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Abstract

We use information on the occupation choices and earnings of immigrants to measure differences in specific skills between workers from rich and poor countries. We have several findings. First, the skills which rich country workers specialize in mirror the skills which high-income individuals specialize in. Second, rich country workers have the greatest advantage in skills related to the ability to generate ideas (like creativity and critical thinking) rather than scientific or technical knowledge. Third, the skills in which rich country workers have the greatest advantage align closely with the skills used in management occupations. Fourth, workers from rich countries are more varied in their skills (e.g., what one Canadian is good at is different from what another Canadian is). These findings do not appear to be accounted for by the non-randomness of immigration or mismeasurement of skills. Overall, our results suggest that rich country workers have skills particularly well-adapted to production processes involving the coordinated efforts of large groups of people.

1 Introduction

Countries vary enormously in their output per capita. Various evidence suggests that a substantial fraction of this cross-country variation in output – perhaps on the

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order of a half, though estimates vary – can be explained by differences in human capital (e.g., Hanushek and Kimko 2000, Hendricks 2002, Caselli 2005, Hsieh and Klenow 2010, Jones 2014, Manuelli and Seshadri 2014, Hendricks and Schoellman 2018).[1]

Given that workers from different countries appear to have different human capital, our paper asks a natural followup question: *What* exactly is different about the human capital of workers from rich and poor countries? Human capital is a vector of different skills – a fact demonstrated by evidence such as the existence of comparative advantage in educational and occupational field choice (e.g., Paglin and Rufolo 1990, Kinsler and Pavan 2015, Kirkeboen et al. 2016, Guvenen et al. 2020, Lise and Postel-Vinay 2020); returns to experience which are specific to firms, industries, or occupations (e.g. Neal 1995, Dustmann and Meghir 2005, Kambourov and Manovskii 2009); imperfect correlations between cognitive competences (e.g., Spearman 1904, Gardner 1983); and the independent predictive value of cognitive and non-cognitive skills for labor market outcomes (see Heckman 2008 for a review). Given there are many skills, which skills, exactly, are more abundant in rich countries? Are workers from rich countries characterized by greater conscientiousness and diligence, perhaps reflecting cultural values about work? Are they better at cooperation? Are they better at abstract reasoning tasks? Or are they distinguished by greater technical knowledge?

While we believe this question is of intrinsic interest, the answer is also potentially informative about *why* rich countries have more human capital. Economists have proposed various explanations for cross-country differences in human capital production, including quantity of schooling (e.g. Barro 1991, Mankiw, Romer, and Weil 1992; see Bils and Klenow 2000 for a critique), quality of schooling (Chiswick 1978, Bratsberg and Terrell 2002, Hanushek and Woessmann 2008, Hanushek and Woessmann 2012, Schoellman 2012), learning on the job (Lagakos et al. 2018a and 2018b), and cultural differences (e.g., Barro and McCleary 2003, Tabellini 2010, Fulford et al. 2020). A complete explanation of skill differences should be able to match not only cross-country differences in an aggregated measure of human capital, but also the specific mix of skill differences.

To answer our question, we study the occupation choices of immigrants to the United States. A worker's occupation is a signal about their skills (Roy 1951); engineers are usually good at math, while journalists are typically good at writing. Using over one hundred measures of occupational skill requirements from O*NET, we measure whether immigrants from high-income countries sort into occupations which require different skills than workers from low-income countries.

High-paying jobs have broadly different characteristics from low-paying jobs, and we would like a more precise finding than one that workers from rich countries are sorting into white collar jobs. To deliver additional precision, we use income-

[1]Differences in technology, defined as a Solow residual, seem to explain most of the remaining variation, with differences in physical capital being less important.

conditional skills as our main outcome measure. Instead of measuring total differences in skill, this measure asks whether the differences in specific skill requirements are larger or smaller than what would be predicted based on the differences in income. We discuss this measure in greater detail in Section 2.

We have several primary findings.

First, we find that the skills which rich country workers specialize in are very closely aligned with the skills which differentiate high-income from low-income occupations. Interestingly, this holds true even after conditioning on income, i.e. among immigrant workers with the same income, workers from rich countries work in occupations with skill requirements typical of higher-paid jobs – a fact which can be explained in part by the interpretation of the income-conditional skills measure, as we discuss in Section 3.

The extent of alignment is notable, because, in a world with multidimensional skill, it is not *ex ante* obvious that the mix of skills produced by growing up in a rich country must very closely mirror the mix of skills which are rewarded in the marketplace in an advanced economy. For example, suppose that there were two skills rewarded in the marketplace, numeracy and literacy, and that rich countries had a human capital advantage only because their education system was better at producing numeracy; then high-earning individuals would be distinguished both by strong literacy and numeracy, while rich country workers would be distinguished only by numeracy.

Second, we find that rich country workers specialize most strongly in ideas – substantially more than they specialize in knowledge. By "ideas," we mean skills related to the generation of new thoughts or approaches. By "knowledge," we mean awareness of existing thoughts or approaches. Rich country workers' greatest advantages are in creativity and critical thinking, while differences in scientific knowledge (e.g. of biology, chemistry, or physics) are more modest.

Third, as an additional way to report our results, we characterize differences in skills by finding the occupation which best matches those differences in skills. So, for example, if we had found that rich countries specialize in skills related to math and detail-orientation but not physical strength, one might say "these are the sorts of skills that accountants use." In Section 3, we formalize a method to select the occupation which best fits our results.

We find that the best-fitting occupations are business management occupations. That is, the greatest differences in skill between rich and poor country workers are among the sort of skills that managers use.

Our finding about the importance of managerial skill is consistent with some findings in the existing literature. Firms in developing countries are on average substantially smaller than in rich countries (e.g., Tybout 2000, Poschke 2018). While factors such as capital misallocation (Hsieh and Klenow 2009) and the structure of technological change (Poschke 2018) likely contribute to this, there are still substantial unexplained differences, and it might be that differences in managerial skill matter as well. Bloom et al. (2013) directly document poor management practices in

India. Our findings also have a possible connection with the view that differences in GDP per capita are due to differences in countries' abilities to make products with complex production processes (Hidalgo and Hausmann 2009). To the extent that complex production processes require managerial skill (Giorcelli 2019), our findings might help explain why wealthier countries are able to maintain an advantage in these products.

To further investigate this story, we ask whether workers from wealthier countries are also more specialized/varied in their strengths, as the complexity view of growth would predict. We find that they are, using two approaches. First, we show that the within-country variance of income-conditional skills is larger for richer countries. Second, we construct a definition of a "lopsided" occupation as being an occupation which has unusual skill requirements among similarly-paid occupations, and show that rich country workers work in more lopsided occupations.

Overall, our results suggest that rich country workers have skill profiles which are especially valuable for complex production processes requiring the coordinated efforts of many people. Ideas can have a greater value in large-scale operations because ideas are non-rival (Schumpeter 1942). Managerial skills are more important in larger organizations. And there is more scope for specialization in complex production processes than in simple ones. We leave it to future research to assess the direction of causation – whether countries are rich because they have the skills to enable complex production processes, or whether instead complex production processes give people the incentive to develop these skills, or both.

There are several reasons why our measurements might not reflect differences in the skills of workers within immigrants' origin countries. One concern is that occupations are a noisy measure of skills. It is clear that there is measurement error simply from the fact that workers within the same occupation do not have identical levels of skill. Using information on earnings *within* occupations, we find that the result of this measurement error is that our main results are most likely attenuated in the direction of zero (i.e., skill differences are larger than our main results imply), but without appreciably impacting the relative ranking of which skills rich countries specialize in the most. We also show that our results are not sensitive to the arbitrary units of skills used in the O*NET data.

A second concern is that immigrants to the United States are not representative of people in their origin country. It is well-known that the decision to immigrate is not random, including with respect to a worker's overall level of skill, and that the extent of this non-randomness varies by origin country GDP per capita (Borjas 1987). We develop two approaches to gauging this problem. One is based on placebo tests among people who immigrate at an extremely young age, on the principle that non-random parents will have non-random children. The other approach is based on comparing countries with low rates of immigration to the US (where immigrants are very unusual) to countries with high immigration rates (where immigrants are likely more representative) to infer the pattern of non-randomness of immigration. Though each of these methods is imperfect, they independently give a broadly consistent picture of the biases introduced by the non-representativeness of immigrants. We find evidence of systematic biases, but unrelated to the main takeaways described above. Furthermore, as an additional robustness check, we find qualitatively similar results when we replicate our research design with data from Brazil, even though immigration to Brazil appears to be non-random in different ways from immigration to the US.

It is important to recognize that skills in our paper are defined as skills used in the United States (or, for some robustness checks, Brazil). Someone who is good at verbal communication in Russia will not necessarily be good at verbal communication in the United States. Our results are based only on the skills which are used in the United States (e.g., ability to write well in English) as opposed to a broader definition of the same skill (e.g., ability to write well in one's native language).

We make two main contributions. First, we provide the richest description of precise skill differences between workers from high- and low-income countries. Perhaps the most detailed description is by Schoellman (2010), who is primarily focused on the difference in skills between natives and immigrants but also notes some differences in a five-dimensional measure of skill between immigrants from high- and low-income countries. Second, we make methodological contributions, especially including the method of reporting skills with the match to the most similar occupation. We argue in Section 3 why this method has advantages compared to existing approaches which rely on researcher-selected aggregations of skills.

The rest of the paper proceeds as follows. Section 2 describes our data sources. Section 3 describes differences in average skill. Section 4 describes robustness checks for these main results. In Section 5, we interpret our main results and describe results related to specialization. Section 6 concludes.

2 Data

Our main data source is the American Community Survey (ACS) over the years 2001-2017.[2] The ACS samples households in the United States who have lived at, or intend to live at, their current address for at least two months. This includes both US citizens and non-citizens. We define immigrants to be individuals who report a birthplace outside the United States, and we assign each immigrant to the country of their birth, e.g. people born in Peru are treated as Peruvians. In a limited number of cases, this will result in what is effectively a misclassification of country of origin, since some Peruvians will have actually spent most of their life, say, in Bolivia.

Our primary analyses restricts to immigrants between the ages of 25 and 60 who immigrated within the last five years.[3] This limits our sample to people whose skill levels have presumably been driven by their origin country environment. Our

[2]We use data provided through IPUMS USA (Ruggles et al. 2020).

[3]The ACS asks respondents what year they "came to live in the United States." If they have immigrated more than once, the most recent year is reported.

analyses are also restricted to individuals who report an occupation and positive income.

We measure birth country GDP per capita PPP using World Bank data. Our primary specifications use GDP per capita in the year that the individual is observed in the ACS, with year dummies absorbing any bias that would arise from comparing earlier to later years of data, but our results are not sensitive to assigning every country a GDP per capita from a fixed year. For a handful of countries, GDP per capita is not available in all years and must be imputed, but the method of imputation does not affect our results.[4]

Consistent with the previous literature (e.g., Hendricks 2002, Hendricks and Schoellman 2018), we find that earnings in the US are higher for immigrants from higher-income countries. A regression of the average log income of immigrants from a country on the origin country's log GDP per capita gives a coefficient of .256, with standard error of .023.[5]

We measure the skill requirements of each occupation using data from the Occupational Information Network (O*NET). O*NET is a United States Department of Labor database designed for job-seekers which describes occupations using a list of over one hundred characteristics describing the type of work performed and the skills and qualifications required to work in that occupation. We focus on occupation characteristics listed under the categories *Skills*, *Abilities*, *Knowledge*, and *Work Styles*. For some of these categories, O*NET provides both a level of skill required and an importance of a skill; we use the importance measure for our primary results, but the results are effectively identical using the level measure instead. This produces a list of 136 characteristics. For simplicity, we will refer to these characteristics as "skills." The skills are listed individually in our results, e.g. in Appendix A.

We merge O*NET data to ACS data on the basis of occupation. In the ACS data, many observations are missing the final digit(s) of the occupation code, which is generally 6 digits long. Because occupation codes are hierarchical, occupations sharing the first 4 or 5 digits generally have very similar skill requirements, so we impute skill values based on the average among occupations sharing the same non-missing digits. The occupation codes used are not consistent across data sets, so some

[4]In some cases information for year 2017 was not available and the latest update available in the World bank database was used. For the countries of Syria (2010), Cuba (2010), Venezuela (2014), Bermuda (2013), and Eritrea (2011), we use the values for the years in parentheses and the year before to calculate a growth rate to then estimate a 2017 approximate value for GDP per capita. Particularly for Cuba and Syria we use information from 2010 from FRED (https://fred.stlouisfed.org/series/RGDPCHCUA625NUPN) because information was not available from the World Bank. For Czechoslovakia, Yugoslavia, and the USSR, all of which no longer exist, we used the population-weighted mean for the countries which have replaced them (e.g., the Czech Republic and Slovakia for Czechoslovakia). Individuals born in England, Scotland, Wales, and Northern Ireland were assigned the United Kingdom measurement of GDP.

[5]Observations are a country in an ACS survey year, giving 2,212 observations. We control for survey year dummies and cluster at the country level. The income variable used here, and in the rest of the paper, is individual wage/salary income.

Table 1: Descriptive statistics

	Mean	Standard deviation
Age	36.00	8.66
Wage and salary income	40,013.50	52,162.54
East Asia & Pacific	0.22	0.02
Europe & Central Asia	0.14	0.02
Latin America & Caribbean	0.41	0.06
Middle East & North Africa	0.04	0.01
North America	0.03	0.01
South Asia	0.14	0.03
Sub-Saharan Africa	0.05	0.01

Note.- Summary statistics for primary sample (ages 25-60, immigrated in the last five years). $N = 255,494$. Region variables are dummy variables equal to one if the immigrant's origin country is in that World Bank region.

crosswalking is required. Finally, we drop observations with military occupations, for which O*NET does not assign skill requirements; this affects .2% of our primary sample.

Income-conditional skills Our primary outcome variables are income-conditional skill measures. To construct these, we first bin workers into deciles of income. Then, among workers within each decile, we estimate the mean and standard deviation of each skill s, and construct the income-conditional level of skill s as the number of standard deviations above or below the average.

The value of using this outcome measure is that, if one simply uses total skills, the measurements will inevitably simply reflect that workers from wealthier countries work in more white collar jobs (DiNardo and Pischke 1997). By contrast, the income-conditional measure allows for a slightly more refined notion of differences in skills by asking whether differences between rich and poor country workers in a particular skill are larger or smaller than would be expected based on differences in income.

In particular, one obtains negative values for skills where differences in skill are smaller than would be expected based on differences in income, and positive values for skills where differences are larger.

A simple model may help readers understand the interpretation of income-conditional skills measures. Suppose that there are two skills, A and B, with worker i's income being

$$y_i = h(a_i, b_i)$$

for some function h which is strictly increasing in both of its arguments. We can think of A as being a skill of interest, and B being its complement in an earnings function, potentially including luck in addition to actual skills.

If workers i and j have the same income (i.e., $y_j = y_i$), but $a_j > a_i$, then it must be that $b_j < b_i$. Figure 1 illustrates graphically; among workers on the same "iso-income" (collection of skill bundles delivering the same income), those who have higher value of A must have lower values of B.

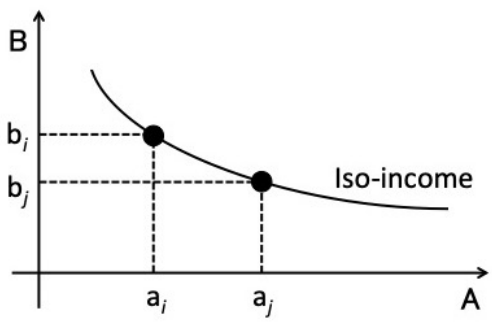


Figure 1: Illustration

Let p_i^A be the percentile of worker i's level of skill A among workers with the same income, and p_i^B be the analogous percentile for skill B. Then $p_i^B = 1 - p_i^A$, because h is increasing in each of its arguments. Therefore, any intervention which increases $E(p_i^A)$ will decrease $E(p_i^B)$ by the identical amount.

In this respect, we can think of income-conditional skills as measuring a relative advantage in some skill, or a skill bias. Increases in B alone will reduce an individual's place in the income-conditional distribution of A.

As we discuss in Section 4, the units of skill measures are largely arbitrary. However, suppose that the distribution of income-conditional A for workers from country c first-order stochastic dominates the distribution of income-conditional A for workers from country c'. Then, for any A' and B' which are increasing transformations of the units of A and B respectively (i.e., which preserve the ranking of which workers are more skilled than which others for each skill), workers from country c will have higher average income-conditional values of A', while workers from country c' will have higher average income-conditional values of B'. Therefore a key target for our robustness checks will be to check for evidence of first-order stochastic dominance of income-conditional skills.

3 Results

We begin by constructing income-conditional skills for each worker in our primary sample. We then aggregate these measures by taking averages at the country-year level (e.g., an observation might be immigrants from Mexico observed in the 2014 ACS).[6]

[6]We drop countries with fewer than 20 total individuals observed.

Let the average income-conditional level of skill s for country c in year t be called $\bar{Z}^s_{ct}$. Furthermore, let $zGDP_{ct}$ be country c's output per capita, in units of number of standard deviations above or below the average of log of output per capita in that year. (For reference, one standard deviation of log of output per capita is equal to 0.82). For each skill s, we then regress $\bar{Z}^s_{ct}$ on the standardized natural log of national GDP (denoted $zGDP_{ct}$) and ACS year dummies (γ^s_t):

$$\bar{Z}^s_{ct} = \beta^s zGDP_{ct} + \gamma^s_t + \epsilon^s_{ct}.$$

Standard errors are clustered by country.

The ten skills with the largest estimated coefficients $\widehat{\beta^s}$ (i.e., the skills where rich country immigrants have the greatest advantage) are shown in Table 2. The ten skills with the smallest (most negative) $\widehat{\beta^s}$ are shown in Table 3. Appendix A contains the full list of estimates across all skills.

Two things stand out from the list of results. The first is that rich countries specialize in producing cognitive skills, i.e. the coefficients for skills related to cognition tend to be positive while the coefficients for skills related to strength or dexterity tend to be negative. (This statement is not based on a formal categorization of skills, but it is obvious from the results that any reasonable categorization would deliver this result.) That is, the advantage that rich countries have in producing cognitive skills is larger than their advantage in producing physical skills.

Second, the largest coefficients are related to the generation and evaluation of ideas. Skills such as Originality and Fluency of Ideas are related to producing new ideas. Critical Thinking involves the ability to assess ideas. And various of the other top skills involve some mixture of generating and assessing ideas on the basis of objectives, such as Systems Analysis, Systems Evaluation, Complex Problem Solving, Active Learning, and Operations Analysis.

This is an interesting contrast with variables related to scientific knowledge. Cognitive work can involve either the ability to produce and evaluate new ideas, as among the variables just mentioned; or it can involve awareness of existing ideas and information, as suggested by the commonly-used term "knowledge economy."[7]

Table 4 lists coefficients and the rank of that coefficient (out of the 136 skills overall) for those skills which we judge to be most closely related to scientific knowledge. While a couple of these coefficients are large, most are more modest.

Alternative specifications Our results are not sensitive to various changes in specification.

[7] Our distinction between ideas and knowledge is related to, but not necessarily the same as, psychologists' distinction between fluid and crystallized intelligence (Cantrell 1992). "Crystallized" intelligence is the ability to draw conclusions based on existing knowledge and experience, while "fluid" intelligence is the ability to reason about novel situations without relying on existing knowledge or experience. The skills we describe as ideas skills seem more closely related to fluid intelligence. However, we lack any psychometric data to confirm this connection.

Table 2: Top ten skills

Skill	Coefficient	Description
Systems Analysis	0.164 (0.015)	*Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes.*
Fluency of Ideas	0.159 (0.013)	*The ability to come up with a number of ideas about a topic (the number of ideas is important, not their quality, correctness, or creativity).*
Originality	0.158 (0.013)	*The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.*
Systems Evaluation	0.158 (0.015)	*Identifying measures or indicators of system performance and the actions needed to improve or correct performance, relative to the goals of the system.*
Complex Problem Solving	0.157 (0.015)	*Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.*
Active Learning	0.150 (0.016)	*Understanding the implications of new information for both current and future problem-solving and decision-making.*
Critical Thinking	0.150 (0.016)	*Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions, or approaches to problems.*
Reading Comprehension	0.149 (0.016)	*Understanding written sentences and paragraphs in work related documents.*
Achievement/Effort	0.147 (0.015)	*Job requires establishing and maintaining personally challenging achievement goals and exerting effort toward mastering tasks.*
Operations Analysis	0.146 (0.011)	*Analyzing needs and product requirements to create a design.*

Note.- List of the ten skills with the largest estimated coefficients from a regression of income-conditional skill usage (in standard deviations) on log of GDP per capita (in standard deviations). $N = 2,212$. Robust standard errors clustered at the country level in parentheses. The right-hand column is O*NET's description of each variable.

Table 3: Bottom ten skills

Skill	Coefficient	Description
Static Strength	-0.150 (0.016)	*The ability to exert maximum muscle force to lift, push, pull, or carry objects.*
Stamina	-0.144 (0.016)	*The ability to exert yourself physically over long periods of time without getting winded or out of breath.*
Trunk Strength	-0.141 (0.015)	*The ability to use your abdominal and lower back muscles to support part of the body repeatedly or continuously over time without 'giving out' or fatiguing.*
Extent Flexibility	-0.137 (0.016)	*The ability to bend, stretch, twist, or reach with your body, arms, and/or legs.*
Gross Body Coordination	-0.137 (0.015)	*The ability to coordinate the movement of your arms, legs, and torso together when the whole body is in motion.*
Manual Dexterity	-0.134 (0.017)	*The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.*
Arm-Hand Steadiness	-0.133 (0.016)	*The ability to keep your hand and arm steady while moving your arm or while holding your arm and hand in one position.*
Speed of Limb Movement	-0.127 (0.015)	*The ability to quickly move the arms and legs.*
Dynamic Strength	-0.126 (0.015)	*Ability to exert muscle force repeatedly or continuously over time. Involves muscular endurance and resistance to muscle fatigue.*
Multilimb Coordination	-0.125 (0.016)	*The ability to coordinate two or more limbs (for example, two arms, two legs, or one leg and one* arm) *while sitting, standing or lying down.*

Note.- List of the ten skills with the smallest (most negative) coefficients from a regression of income-conditional skill usage (in standard deviations) on log of GDP per capita (in standard deviations). $N = 2,212$. Robust standard errors clustered at the country level in parentheses. The right-hand column is O*NET's description of each variable.

Table 4: Scientific knowledge skills

Skill	Coefficient	Rank (out of 136)
Knowledge of Geography	0.141	12th
	(0.011)	
Knowledge of Mathematics	0.115	34th
	(0.013)	
Knowledge of Engineering and Technology	0.086	52nd
	(0.010)	
Knowledge of Physics	0.049	69th
	(0.009)	
Knowledge of Biology	0.039	74th
	(0.010)	
Knowledge of Psychology	0.012	83rd
	(0.016)	
Knowledge of Chemistry	-0.014	91st
	(0.010)	
Knowledge of Medicine and Dentistry	-0.053	107th
	(0.016)	

Note.- List of coefficients for skills related to scientific knowledge. Robust standard errors clustered at the country level in parentheses. The right-hand column gives the rank of the estimated coefficient out of 136 skills s for which we estimate β^s, with 1st being the largest coefficient and 136th the smallest.

Because our results could be influenced by a correlation between origin country GDP per capita and age at time of immigration, we replaced income-conditional skills with income-conditional skills residualized on age and age squared before taking national averages. The results produced in this way are so indistinguishable from our main results as to be effectively identical: Across all skills, the correlation between $\widehat{\beta}_1^s$ with these controls and $\widehat{\beta}_1^s$ without them is greater than .99.

Similarly, our results are not sensitive to the number of bins of income used to construct income-conditional skills. We obtain effectively identical results across a range of number of bins of income, or when residualizing skills on log income within each bin prior to standardizing and taking country averages.

Aggregating to an average income-conditional skill level for each country across all years (as opposed to by year of the ACS) and using a single value of log GDP per capita for each country (created by averaging over all years of log GDP) produces results which are also virtually identical to our main results (correlation greater than .99).

Adding a control for the origin country's region in our main regression gives results which have a correlation of .98 with our main results.[8]

For skills where both a level and importance of a skill are available in the O*NET data, our main results are based on the importance measure. The correlation between our main results and the results using the level measure instead is 0.99.

Finally, we imputed GDP per capita for some country-years, due either to missing World Bank data (e.g. because of war in Syria) or because of changing national boundaries (e.g. some respondents list Czechoslovakia as their country of birth). We again obtain effectively identical results dropping any or all of these countries.

3.1 Closest occupation

Because we are producing estimates for over 100 different skills, it is helpful to aggregate the results using simple summary measures. The standard approach is to group skills into a small number of indices, e.g. of cognitive skill or social skill, chosen by the researcher. Indeed, our description of results above, in which we emphasize the importance of ideas as opposed to knowledge, loosely follows this approach. Some downsides of this approach, though, are that (i) it inevitably focuses on a handful of skills to the exclusion of describing others, thereby throwing away most of the available information, and (ii) the reporting of results is influenced by subjective choices made by the researcher.

To solve these problems, we next develop a method for reporting skill differences in terms of a closest occupation. Suppose that we had found that workers from rich countries had the greatest advantage in mathematical skills and attention to detail. Then one might say "these are the sorts of skills that accountants use." By contrast, if workers from rich countries had their greatest advantage in persuasiveness and

[8]We use the World Bank classification of regions.

verbal communication, one might say "these are the kinds of skills that marketers use." The procedure below finds the occupation which is the closest fit to the sort of skills for which we observe rich country workers to have the greatest advantage.

This approach has the advantages that (i) it captures information about the full range of skills for which we have data, (ii) it is relatively "nonparametric" (figuratively speaking), in the sense that the model is not constrained to choose from a very small number of possible results which are pre-imposed by researcher choices,[9] and (iii) it nonetheless produces a result which is interpretable, since most people have a sense of the skills required by most occupations.

Note that, just as our main results use income-conditional skills, we will define an occupation's skills in terms of that occupation's *income-conditional* skill requirement, i.e. what distinguishes workers in that occupation from workers with a comparable overall level of income.

The procedure is as follows. For each occupation j, we construct the average income-conditional skill of immigrants workers in occupation j.[10] Let Occ_j^s be this average for skill s. Similarly, our main results above produce an estimated coefficient $\widehat{\beta}^s$ for each skill s. We select the nearest-fitting occupation j and a scalar multiple λ to solve the following minimization problem:

$$\min_{\lambda \geq 0, j} \sum_s \left(\widehat{\beta}^s - \lambda Occ_j^s \right)^2 .$$

The expression to be minimized will be smallest, for example, if Occ_j^s is exactly a positive scalar multiple of β^s.

The choice of j can be interpreted as "the set of skills here are the sort of skills used by people in occupation j," while λ describes an intensity, with larger λ indicating a stronger magnitude of skill bias in the direction of the sort of skills used in the selected occupation. We constrain λ to be positive such that we are looking for occupations which resemble rich country workers' skills.

We solve this minimization problem in two steps. First, for each occupation j, we find the λ_j that minimizes the expression

$$\sum_s \left(\widehat{\beta}^s - \lambda_j Occ_j^s \right)^2 .$$

This can be done simply by regressing $\widehat{\beta}^s$ on Occ_j^s while omitting the constant, where an observation in this regression is a skill s. The resulting coefficient on Occ_j^s is the best-fitting λ_j. We constrain to $\lambda_j \geq 0$ by dropping occupations with negative λ_j, but this constraint is not binding for the best-fitting occupations.

[9]This agnosticism might be a disadvantage in a context where the researcher has more specific hypotheses to investigate, but is advantageous in a context like ours where the goal of our empirical exercise is exploratory and descriptive.

[10]As before, income-conditional skills are in units of standard deviations above or below the average. Occupations are defined as unique O*NET occupation codes, which can sometimes correspond to multiple occupations in the ACS occupation codes.

Table 5: Best-matching occupations

Occ. code	Occ. name	$\widehat{\lambda_j}$	R-squared
13-108	Logisticians	0.085	0.657
11-101	Chief Executives	0.076	0.654
25-101	Postsecondary Teachers	0.060	0.609
11-919	Managers, All Other	0.128	0.591
11-202	Marketing and Sales Managers	0.079	0.587

Note.- List of the five O*NET occupations with best fit (highest r-squared) to the main results (estimates of β^s). $\widehat{\lambda_j}$ is the estimated value of λ_j. See text for details.

Second, we select the j which minimizes the objective function, given we know from the first step what λ_j would be. This can be done simply by noting the r-squared of the above regression for each occupation j, and selecting the j with the highest r-squared.[11]

Table 5 reports the top five occupations which minimize this squared error, along with the best-fitting λ_j for that occupation and the r-squared of the regression.

The results suggest that the skills of rich country workers are like the skills of managerial-related workers. The best-fitting occupation is Logisticians, and the next-best fits are also closely related with business management.

The r-squared tells us how closely this description matches the full set of skill biases. The r-squared of roughly .66 means that the description that "the skill bias here is in the direction of managers' skills" fits our results to a substantial extent. In particular, there is a correlation of $.657^{1/2} = .81$ between our main results and the income-conditional skills of Logisticians.

3.2 Correlation with high-earners' skills

The skills of rich country workers that we obtain from our main results also closely resemble the skills of high-earning workers in general. To demonstrate this, we estimate the regression

$$Z^s_{it} = \alpha^s Inc_{it} + \xi^s_t + \nu^s_{it},$$

where i denotes an individual, t denotes a survey year, Z^s_{it} is the number of standard deviations above or below the average that the individual is for their occupational

[11] Choosing the occupation with the highest r-squared gives the minimum of the objective function because, across all j, the variation in β_s to be explained is the same. Therefore, the occupation j which explains the greatest fraction of variation in β_s will also have the smallest sum of squared residuals.

skill usage (relative to the entire sample in that year, i.e. not income-conditional), Inc_{it} is the respondent's income, and ξ_t^s represents ACS year dummies. To avoid mechanical correlation with our main results, we restrict this regression to native-born workers between the ages of 25 and 60, i.e. not including anyone used in our main analysis.[12]

The results are very strongly correlated with our main results: The correlation between our estimates $\widehat{\alpha^s}$ and $\widehat{\beta^s}$ is .93. That is, the skills which differentiate rich country workers from poor country workers – even conditional on earning the same amount – closely resemble the skills which differentiate high-earning natives from low-earning natives.

It is important to note one potential contributing factor to this result, which is the role of luck in earnings. It has long been known that workers' earnings seem to be driven in part by factors unrelated to their skill or productivity (Slichter 1950). Suppose there is some difference between how much someone makes and how much they might have been expected to make based on their level of skill; call this difference *luck*. High earners will be on average more lucky than low earners, for the reason that luck increases earnings. If rich country workers are not more lucky than poor country workers, but have higher earnings due to differences in skills, then they will tend to have low income-conditional luck. Because they have low income-conditional luck, it follows that they must have high income-conditional skill (see the model in Section 2). This may help explain why most estimates $\widehat{\beta^s}$ are positive, and may contribute to the alignment of $\widehat{\beta^s}$ with $\widehat{\alpha^s}$.

4 Robustness

The previous section describes differences in occupational skill usage between immigrants to the US from rich and poor countries. A natural question is whether this accurately describes differences in skills of workers who remain in the origin countries.

There are two central issues which might lead our measurements not to reflect differences in skills between workers from rich and poor countries generally. The first is that we might mismeasure workers' skills. The second is that, even if we successfully describe differences in immigrants' skills, these differences might be due to the non-randomness of immigration rather than differences in the skill levels of origin country populations.

[12]Mechanical correlation would arise because individual workers from rich countries earn more on average than workers from poor countries. For computational reasons, we also estimate this regression using a random 10% subsample.

4.1 Measurement error in skills

There are three primary concerns about mismeasurement of skills. The first is about whether measures of skill are context-specific, e.g. whether someone is good at communication might depend on who they are supposed to communicate with. The second is that our measure of skills is noisy, in that workers within the same occupation do not all have the same level of skill. The third is that the units of skill measurements are arbitrary. We discuss each of these in turn.

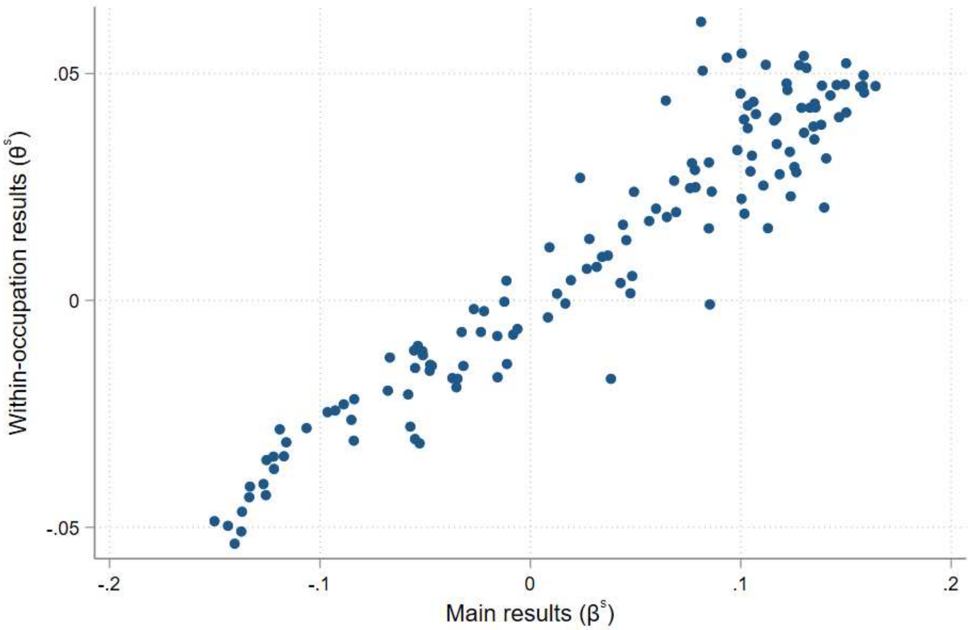
Location-specific skills Skills are to some extent location-specific. For example, in the US, verbal communication effectively means the ability to communicate in English. This is a less important skill in, say, Japan; there, ability to communicate in Japanese is more important. To the extent that we measure differences in verbal communication by nation of origin, it is therefore unclear whether this reflects differences in general communication ability (e.g. the carefulness with which people organize their thoughts) or whether it simply reflects the extent to which the communication skills required in a worker's origin country are aligned with the communication skills needed in the US.

This problem of skill transferability is a source of measurement error to the extent that a variable labeled as "verbal communication" would not reflect the relevant notion of verbal communication for understanding output in non-US contexts. But this is not a source of measurement error if we conceive of skills as being the US versions of the measured skills. Therefore, our results should be interpreted as reflecting differences in the US versions of the measured skills.

Occupation as imperfect skill proxy Workers in the same occupation do not have identical skill levels; therefore, occupation cannot possibly be an exact measure of skill (e.g., Deming and Kahn 2018). Furthermore, at the level of individual origin countries, there is often clustering in certain occupations arising due to social networks in job search rather than match quality, especially among low-skill occupations (e.g., Waldinger 1994, Patel and Vella 2013). Our results would be biased if the measurement error from using occupation as a proxy for skills is correlated with output per capita of an immigrant's origin country. Examples of mechanisms which might create such systematic correlation are licensing requirements which are easier to satisfy for immigrants from rich countries, or employer discrimination in screening applicants (Oreopoulos 2011).

To address this, we additionally measure how the earnings premium for rich country workers *within* an occupation varies according to the skill requirements of the occupation. If our results are driven by one of these barriers to entry, then only the best poor country workers will make it into occupations which we label as requiring rich country skills. Therefore, poor country workers would look strongest relative to rich-country occupational peers when working in occupations that our main results describe as being intensive in rich country skills. Blair and Chung

Figure 2: Within-occupation coefficient estimates and main results



Note.- Scatterplot of $\widehat{\theta^s}$ against main results ($\widehat{\beta^s}$). Each point represents a skill s.

(2020) provide a formal model of this mechanism.

To investigate whether this is the case, for each occupation j, we regress individual earnings on log of origin country GDP per capita for every worker in that occupation. Call the resulting coefficient estimate $\widehat{\alpha_j}$ for occupation j. Then, for each skill s, we estimate the regression

$$\widehat{\alpha_j} = \psi^s + \theta^s Occ_j^s + \nu_j^s.$$

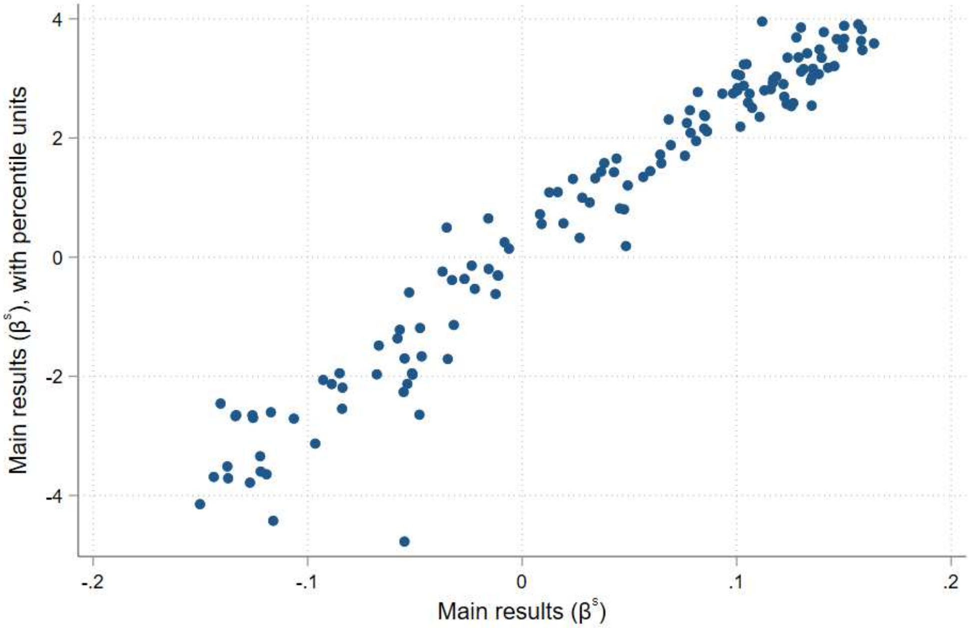
Figure 2 plots the resulting within-occupation coefficient estimate $\widehat{\theta^s}$ against the main result coefficient $\widehat{\beta^s}$ for each skill s. Two things are notable.

First, skills with larger $\widehat{\theta^s}$ also have larger $\widehat{\beta^s}$. That is, rich countries workers have the greatest within-occupation earnings advantage in occupations which use what our main results imply are rich-country skills. This suggests that our main results are more likely to be understated than overstated.

Second, there is a tight relationship between $\widehat{\theta^s}$ and $\widehat{\beta^s}$. (The correlation is 0.95.) This suggests that, while the use of occupation as an imperfect skill proxy might affect the absolute magnitude of our results, it likely does little to change the *relative* magnitudes, i.e. this would not distort the ranking of skills given by our main results.

Arbitrary units Skills do not have well-defined units. The O*NET measures of skill are based on questionnaires which score aspects of job requirements on a 1-7 scale, but there is no reason why the difference between a 1 and a 2 should be

Figure 3: Results under percentile units



Note.- Scatterplot of main results ($\widehat{\beta^s}$) using income-conditional percentile units against results in income-conditional standard deviations. Each point represents a skill s.

considered "the same" as the difference between a 2 and a 3 for any given skill. In this respect, skill measures might be understood as being ordinal as much as cardinal. This can potentially make our results sensitive to an alternative rank-preserving measure of skill. However, in Section 2, we showed that, if there are shifts throughout the distribution of income-conditional skills, our results would not be sensitive to such rank-preserving changes.

We investigate the possible sensitivity of our results in two ways. First, we run our results by measuring income-conditional skills using a percentile within a bin of income (analogous to p_i^A in Section 2), rather than a number of standard deviations above or below the average. Figure 3 shows the relationship between coefficients estimated in this way and our main results. The correlation is .97.

Second, based on the discussion in Section 2, we replace our baseline measure of income-conditional skills with dummies for whether an individual is at least at the 25th, 50th, or 75th percentile of usage of skill s among workers in the same income bin. In general, skills with positive $\widehat{\beta^s}$ have positive coefficients for the probability of being at least at all three of these percentiles. The correlations with our main results for these three percentiles are .91, .94, and .94 for the 25th, 50th, and 75th percentiles, respectively.

These findings suggest that our main results are not likely to be sensitive to alternative ways of measuring skill which preserve the same ordinal ranking.

4.2 Non-random selection of immigrants

Another reason it might be difficult to draw conclusions about the skills of workers within rich and poor countries based on our study of immigrants is that immigrants to the United States are a non-random sample of workers from their origin country.

It is not necessarily a problem if immigrants are unrepresentative, so long as they are equally unrepresentative in rich as in poor countries. However, if immigration is differently non-random with respect to skill levels in rich versus poor countries, it will bias our estimates of skill differences between rich and poor countries.

Two factors lead to non-randomness. The first is that not everyone wishes to move to the US. The second is that, thanks to immigration laws, not everyone who wishes to move is able to.

A brief description of US immigration laws may help readers understand the second factor. Foreign-born workers who would be present in the US and therefore potentially included in our sample can be in the US either (i) as permanent residents (roughly 13.6 million people as of 2019), (ii) on non-immigrant visas (roughly 2.3 million, of whom roughly half are temporary workers, as opposed to students or diplomats), or (iii) illegally (estimated to be roughly 12 million as of 2015, though many have been in the US longer than five years and therefore would not be in our primary sample).[13] Some of the recently-arrived workers in our data might also be US citizens – for instance, if they obtained permanent residence via marriage to a US citizen and chose to naturalize after three years (other forms of permanent residence require five years of residence before naturalizing), or if they were a US citizen at birth due to the citizenship of their parents. Note that the fractions of immigrants within each of these categories might not equal the effective weight in our main results, since our main results aggregate by country.

There are four primary ways to obtain permanent residence (commonly referred to as a "green card") in the US. The most common, accounting for roughly 70% of new permanent residents in recent years (Department of Homeland Security 2019),[14] is through family ties (generally because a spouse, parent, child, or sibling is a citizen or permanent resident). It is also possible to obtain a green card as a refugee or asylee, which accounts for somewhat over 10% of green cards. A third category is employment-based immigration, which also accounts for slightly over 10% of green cards. Workers who obtain a green card through their job are generally selected to be skilled workers. There is also a green card lottery, which accounts for roughly 5% of green cards. This "diversity lottery" is open to all workers with at least a high school education and/or two years of experience in an occupation requiring at least two years of training, provided that these workers come from a country

[13] See Estimates of the Lawful Permanent Resident Population in the United States: 2015-2019, DHS; Nonimmigrants Residing in the United States: Fiscal Year 2016, DHS; and Estimates of the Unauthorized Immigrant Population Residing in the United States, DHS.

[14] See Table 6 of the DHS 2019 document for specific breakdowns of recent green card approvals, and see prior DHS yearbooks for comparable statistics showing a stable pattern of reasons for granting green cards in other recent years.

which has sent fewer than 50,000 immigrants to the United States in the last five years. A formula determines the number of visas made available for each region of the world (e.g. Europe); all eligible applicants from the same region have the same probability of winning. Finally, a small fraction of green cards are accounted for by other miscellaneous categories (e.g. Iraqis and Afghans employed by the US government during wars in those places). Additionally, immigrants may work in the US without having obtained permanent residence, typically by obtaining an H-1B, L-1, O-1, E-1, or TN visa.[15] The largest of these non-immigrant visas, the H-1B, accounts for an influx of roughly 150,000 workers per year over the time period studied, as opposed to in excess of 1 million green cards given per year. Therefore, the number of workers given nonimmigrant visas via the H-1B is similar to the number of workers who obtain a green card on the basis of employment status – and indeed, a large fraction of H-1B holders go on to obtain permanent residence. In sum, the most common basis for immigration is a family connection to an existing US citizen or permanent resident, though employment-based immigration accounts for a substantial minority.

One scenario which would produce differential non-randomness is if workers from poor countries are disproportionately likely to be constrained by immigration laws, while workers from rich countries are more likely to choose not to immigrate because they simply do not wish to. In this case, because there are different mechanisms generating non-randomness, workers from rich countries might be differently representative of their home country than workers from poor countries.

As a simplified example, suppose there were an immigration law that workers could only immigrate if their cognitive skills were above a certain threshold. Furthermore, suppose that average cognitive skills are lower in poor countries. Then immigrants from poor countries will be selected for having unusually high cognitive skills, while immigrants from rich countries will be more representative of their home country. In this case, the differences in cognitive skills among immigrants would be attenuated relative to the true differences in cognitive skills in the origin country populations.

We perform three main robustness checks to investigate whether this or any related bias exists.

Immigration rates Non-randomness of immigration only biases our results to the extent that (i) the propensity to immigrate is correlated with skills, and (ii) the bias generated by this correlation is different in rich countries than in poor countries – either because the correlation between propensity to immigrate and skills, or the threshold propensity at which immigration occurs, differs by origin country GDP per capita.

[15] The ACS uses a two-month residence rule, i.e. survey respondents must have lived or plan to live for 2 months at their current address to be included in the sample. See more details at https://www.census.gov/content/dam/Census/library/publications/2009/acs/ACSResearch.pdf.

In countries where only a very small fraction of the population immigrates to the US, immigrants must have a very unusual propensity to immigrate. By contrast, in countries where the fraction of people immigrating to the US is high, immigrants are more representative of the general population in terms of their propensity to immigrate. We would therefore expect any bias due to non-randomness to be especially severe in countries with low rates of immigration to the US.

We construct a country's immigration rate as the ratio between the number of immigrants from that country who are observed in the ACS (restricted to immigrants between ages of 25 and 60) to the country's population.

First, we assess whether immigration rates are systematically different from rich and poor countries. Regressing immigration rate on log of GDP per capita, we cannot reject that immigration rates are the same for rich and poor countries (coefficient is -0.0012, standard error is 0.0012, $p = 0.31$).

Second, we ask whether the correlation between income-conditional skills and propensity to immigrate is systematically different in rich and poor countries. To assess this, we estimate the following regression for each skill s:

$$\bar{Z}^s_{ct} = \rho^s RateImm_c * Low_c + \omega^s RateImm_c + \iota^s Low_c + \tau^s_t + \pi^s_{ct},$$

where *Low* is a dummy variable equal to 1 if the country's GDP per capita is below average and 0 otherwise.

The coefficient of interest is ρ^s, which reflects differences in how skill s varies with immigration rate in low-income as opposed to high-income countries. On the principle that high immigration rates mean that immigrants are more representative, ω^s reflects a difference between origin country populations and immigrants in high-income countries, with positive values of ω^s indicating that the origin country population has a higher value of s than immigrants, i.e. immigrants have an unrepresentatively low value. Similarly, ρ^s reflects additional differences in unrepresentativeness in low-income countries. Positive values of ρ^s indicate that immigrants from low-income countries have a more unrepresentatively low value of s (relative to the origin country population) than immigrants from high-income countries.

Recall that the source of bias in our main results is not unrepresentativeness of immigrants, but *differential* unrepresentativeness of immigrants from rich vs. poor countries. When ρ^s is not equal to 0, this suggests such differential unrepresentativeness in income-conditional skills. In particular, because positive values of ρ^s suggest that immigrants from poor countries have more unrepresentatively low values of s, then positive values of ρ^s suggest that β^s is larger than it would be if immigrants were randomly selected from their home country population. Speaking loosely, this means that positive values of ρ^s mean that β^s is probably "overestimated" while negative values mean that β^s is probably "underestimated."

Consistent with prior research (e.g., Borjas 1987) we find that there are differences in the extent to which immigrants from rich and poor countries are non-randomly selected. The full list of coefficients is reported in Appendix B. A large number are statistically significant.

However, this non-randomness does not seem to drive our main takeaways from our results. We give a full description in Appendix B. First, the estimates of ρ^s for ideas-related skills are not larger than for knowledge-related skills. Second, the estimates of ρ^s are not correlated with managerial-related skills. Third, our estimates of ρ^s suggest that the correlation between β^s and the individual-level parameter α^s is, if anything, likely understated due to the unrepresentativeness of immigrants. Instead, it appears that the most important effect of non-randomness is that it leads our main results to understate differences in social skills and dependability.

It is important to note that ρ^s is an imperfect measure of bias due to non-randomness of immigration. Workers from countries with high and low immigration rates might have different skills, which this exercise would incorrectly interpret as non-randomness. Similarly, countries with higher and lower immigration rates might have a different correlation between workers' skills and their propensity to immigrate, and therefore immigrants from these countries might differ not just because immigrants from high-immigration countries are in general less selected, but because such immigrants are differently selected. If either of these correlations exist and exert differential influence among rich and poor countries, then this exercise will have some bias in assessing how non-randomness in immigration biases our results.

Children of immigrants Next, we look at skill bias among individuals who immigrated to the US between the ages of 0 and 2. These individuals are generally the children of immigrants but have little exposure to their origin country environment. Therefore, they allow us to conduct an approximation of a placebo test for whether our estimates are biased by the non-randomness of immigration.

Most traits are heritable, such that there is substantial correlation between traits of children and parents (e.g., Plomin 2019). If the immigration system selects immigrants such that e.g. immigrants from poor countries are selected for being high in knowledge and immigrants from rich countries are selected for being critical thinkers, then we would expect their children to exhibit similar patterns. This is especially true to the extent that, as previously discussed, family ties are easily the most common basis for legal immigration; any non-randomness that this induces would likely show up as a skill bias among young immigrants.

We assess the non-randomness of young immigrants by estimating our main regression, but performing all calculations using people between the ages of 25 and 60 who immigrated at ages 0-2, rather than those who immigrated within the last five years. We will use $\widehat{\widehat{\beta}}^s$ to denote the resulting estimate of the coefficient on $zGDP$ for skill s.

There are again several important caveats to this analysis. First, immigrants who brought young children with them might not be representative of all immigrants. If so, we are learning only about the non-randomness of immigrants who had children. Second, this analysis is historical, in the sense that it measures non-randomness of immigration at the time that the respondents were 0-2 years old. Given the respondents are now adults, this is backwards-looking. Third, some traits are more heritable than others, which might skew the relative ranking of skills produced by this measure. Finally, children who immigrate at very young ages are to some extent exposed to the experiences which shape the human capital of people from their origin country. This is true both because these immigrants receive some inputs prior to arriving in the US, and because immigrant families do not immediately assimilate, and therefore young immigrants continue to have cultural exposure to their origin country even after migration (e.g., Borjas 1992, Dustmann and Glitz 2011, De Philippis and Rossi 2020). The effect of these biases is that this measure should be biased in the direction of labeling results as stemming from non-randomness which actually result from differences in origin country culture and environment.

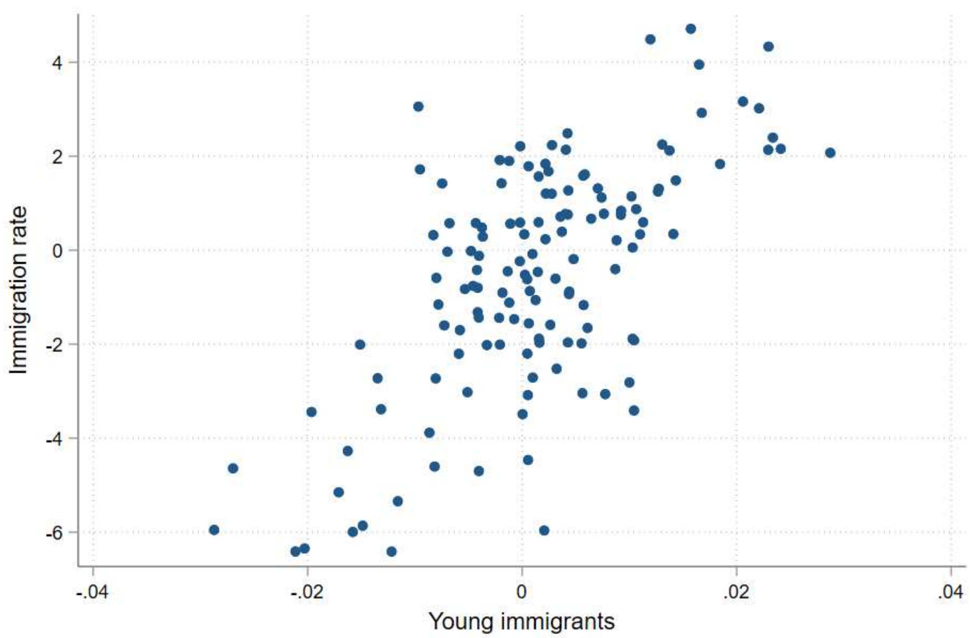
The full set of results of this robustness check are described in Appendix B. We once again find evidence of non-randomness, this time somewhat in the direction of our main results: The correlation between $\widehat{\beta}^s$ and $\widehat{\widehat{\beta}}^s$ is 0.29. However, the magnitudes of $\widehat{\widehat{\beta}}^s$ are far smaller than of $\widehat{\beta}^s$, with the former having a standard deviation of 0.010 and the latter having a standard deviation of 0.093. Further, while there is some alignment with our estimates generally, the extent of alignment does not seem strong enough to account for our key punchlines. The strongest statement that can be made against the main results is that there is some evidence that the young immigrants measure is positively correlated with managerial skills and the skills of high earners – though, in each case, the strength of correlation is modest enough that bias in β^s would likely have the effect of decreasing the correlations measured between our main results and these types of skills.

Although both this analysis and the immigration rate analysis have a considerable list of caveats, the caveats to the two methods are unrelated, and therefore the mistakes made by these methods are likely to be independent as well. Nonetheless, these two methods give a partially (though not entirely) consistent view of how non-randomness might affect our results. Figure 4 plots the estimates $\widehat{\rho}^s$ against $\widehat{\widehat{\beta}}^s$ for each skill s. The correlation between these two estimates is 0.66, suggesting substantial agreement.

Brazilian data Lastly, we reproduce our main results using data from the 2010 Brazilian census, which also contains information on detailed occupation, income, and country of birth.[16] The rationale for this robustness check is that immigrants to Brazil are presumably differently selected than immigrants to the United States. We anticipate differences in selection of immigrants because (i) the factors which attract someone to live in Brazil might be different from the factors attracting someone to live in the US, (ii) because immigration laws differ by country (e.g., Brazil allows residents of most other South American countries to immigrate with nearly no restrictions),

[16]We use data from IPUMS USA: Version 10.0 [dataset]. Minneapolis: IPUMS, 2020. https://doi.org/10.18128/D010.V10.0

Figure 4: Concordance of non-randomness tests



Note.- Scatterplot of immigration rate-based test for non-randomness ($\widehat{\rho^s}$) against young immigrants-based test for non-randomness ($\widetilde{\widehat{\beta^s}}$). Each point represents a skill s.

and (iii) because even superficially similar rules allowing family-based immigration have substantially different impacts in Brazil than in the US due to different historical patterns of immigration.

For a variety of reasons, we consider our US estimates to be more reliable. The primary issue is that the Brazilian data contains very few origin countries with adequate sample to perform our analyses given sample restrictions – for our main results, in which we restrict to using data from countries with at least 20 workers between the ages of 25 and 60 who immigrated within the last 5 years, only 17 countries. As a consequence, the Brazil results are far less precise. Another shortcoming of the Brazilian data is additional measurement error: O*NET's measures of occupational skills were designed to measure skill requirements in the United States, which might not be the same as skill requirements in Brazil, and we must crosswalk occupation codes between the Brazilian data (which codes occupations using the ISCO-08 classification) and O*NET. However, we believe that the Brazilian results are still potentially informative.

The results from Brazil are described in Appendix C. The results are similar to the results in the US; the correlation between the coefficient on a particular skill in the US and in Brazil is 0.78. The primary takeaways from the US data are also present in the Brazilian data.

We also perform the young immigrants robustness check described above. (The sample of countries is too small to perform the immigration rate-based robustness check.) Consistent with the view that immigration to Brazil is characterized by different forms on non-randomness than immigration to the US, our estimates of non-randomness via young immigrants for Brazil do not match up closely with the US estimates (correlation of -0.17 with the same measure in the US). Furthermore, as we discuss in Appendix C, our methods of detecting non-randomness are predictive of whether our main estimate β^s for a given skill s will be larger in the Brazilian or the US data.

Summary of non-randomness robustness checks We emphasize that each of the robustness checks described above is imperfect, and therefore we cannot be completely confident of the extent to which our main results are contaminated due to non-randomness of immigration. However, the balance of evidence described above suggests that non-randomness of immigration is unlikely to fully explain our main results. In particular, the robustness checks do not support the view that the primary takeaways of our main analysis – the alignment with the skills differentiating high- and low-earning individuals, the importance of ideas relative to knowledge, and the substantial difference in managerial skills – are driven by non-randomness.

5 Discussion

While the primary goal of our paper is simply to document differences in skills, it is also helpful to think about how we might understand these results.

One possible interpretation is that immigrants from rich countries (and likely workers from rich countries in general) have skills which are particularly well-suited to the technological environment of rich countries.

It is obvious that the value of skills is context-dependent. A hunter-gatherer, dropped in the middle of New York City, presumably would not outearn the average American. Yet, left in the woods by themselves, the same hunter-gatherer would likely fare better than the average American. This is because both hunter-gatherers and Americans have acquired particular sets of skills which are well-suited for their environment. The issues of skill transferability mentioned in Section 4 also relate to this point; linguistic skills which are well-suited to living in Japan might not translate to the United States.

The alignment of $\widehat{\beta}^s$ with $\widehat{\alpha}^s$ suggests that rich country workers specialize in the sorts of skills which are well-rewarded in economies similar to the US.

While skill prices such as α^s are determined in part by supply, we can see that there are technological reasons why the skills we find to be more common among rich country workers might also be in higher demand in rich countries. Relative to poor countries, rich countries produce more complex goods (Hidalgo and Hausmann 2009) in larger firms (e.g., Tybout 2000, Poschke 2018) which are closer to the technological frontier (Jones and Romer 2010, Poschke 2018) and invest more in R&D (Arkolakis et al. 2018). Each of these features may make the forms of human capital from Section 3 particularly practical.

Managerial skill is presumably more important in contexts where there are people to manage. Larger firms require the coordination of the efforts of many people. More complex production processes, involving more people playing more specialized roles, require managerial skill to coordinate the efforts of people doing more distinct tasks.

Demand for ideas-related skills is also likely to be higher in rich country economies. Ideas are less important in very small businesses, perhaps because the fixed cost of coming up with an idea is divided by relatively few units of production (Schumpeter 1942). Though the literature is unclear about whether medium or large firms are more innovative (e.g., Symeonidis 1996), the smallest firms rarely devote any resources to R&D. There are large differences in the probability of working in the smallest firms by GDP per capita; for example, in Ethiopia manufacturing microenterprises account for 97 percent of employment while in the United States microenterprises account for 26 percent of private sector employment (Li and Rama 2015). Furthermore, there is some evidence that features of the economic environment which increase the optimal scale of firms also lead to increases in innovation (Pagano and Schivardi 2003).

Beyond firm size, firms in advanced economies are more likely to be at the technological frontier, and therefore must innovate to gain a technological advantage, rather than simply imitating existing technologies (Jones and Romer 2010). This would also raise the value of idea-generating skills. The fact that rich country firms spend more on R&D (Arkolakis et al. 2018) also suggests that there might be higher demand for idea-generating skills in rich countries – though of course these expenditures might be endogenous to the supply of labor with idea-generating skills.

Specialization To explore the hypothesis that rich country skills are well-adapted to rich country technologies, we generate a prediction based on this view and test it.

Our prediction is that workers from rich countries should have more specialized skills than workers from poor countries. The sort of complex production processes which are more prevalent in rich countries involve a greater degree of specialization of workers into roles. Hidalgo and Hausmann (2009) argue that advanced economies are able to effectively possess more knowledge about the world by assigning different knowledge and skills to different people – e.g., for consumers to be able to purchase toothpaste, it suffices that *someone* knows how to make it, so it is just as well that only a few people know how to make toothpaste while other people focus on knowing other things.

Therefore, if rich country workers have human capital matching the technological demands of advanced economies, we would expect rich country workers to have more specialized human capital, in the sense they should be more (i) varied and (ii) narrow in their strengths.

Our first test is whether the within-country variance of income-conditional skills is higher for rich countries. This within-country variance is constructed as

$$var_c := \frac{1}{S}\sum_s \left[\frac{1}{N_c - 1}\sum_{i\in C}\left(Z_i^s - \frac{1}{N_c}\sum_{j\in C} Z_j^s\right)^2\right],$$

where Z_i^s is individual i's income-conditional (standardized) skill s, C is the set of individuals from country c, N_c is the number of individuals from country c, and S is the total number of skills. That is, we construct the sample variance of income-conditional skill for each skill, then take the average of this variance across all skills.[17]

Finally, we regress var_c on log of GDP per capita. The results are shown in Table 6.

Our second test is to ask whether workers from rich countries work in more lopsided occupations, i.e. occupations where workers specialize narrowly in being great at only a few things rather than being good at many things. As an example, professional basketball players are quite unusual relative to most high-earning workers, both because their occupation has an unusually high requirement for physical skills and because their occupation has an unusually low requirement for cognitive skills.

We operationalize this notion of "lopsided" as follows. First, we divide occupations into deciles of average income. Next, among occupations within each decile, we

[17] We eliminate observations with only a single observation from a country in a given survey year, since the sample variance would otherwise be 0.

Table 6: Regression of variance on log of GDP per capita

Variance results	
Log of GDP per capita in origin country	0.0220 (0.0054)
Observations	2,175
Lopsidedness results	
Log of GDP per capita in origin country	0.0185 (0.0050)
Observations	2,212

Standard errors in parentheses clustered at the country level.

calculate how many standard deviations above or below the average each occupation j is for each skill s. Lastly, we compute the extent of lopsidedness in occupation j, denoted as L_j, as the sum of the squares of these deviations across all skills. This credits an occupation as having unusual skill requirements if either its skill requirements are unusually high or unusually low.

We then take averages of L_j among workers from each country in each year of the ACS, and use this as an outcome variable in regressions which are otherwise identical to those used in producing our main results. The results are shown in Table 6.

Both sets of results suggest that workers from high-income countries develop more varied forms of human capital, rather than all accumulating the same skills. Workers sorting into occupations which provide them a comparative advantage can in principle lead to higher apparent human capital in rich countries.

However, it is difficult to interpret magnitudes in the above results, so they should properly be considered only to be suggestive. While the results support the view that workers in rich countries engage in a greater degree of specialization of human capital, we cannot say from these results whether this mechanism is quantitatively important in explaining the higher apparent human capital of workers from rich countries.

6 Conclusion

We measure skill differences between workers from rich and poor countries. We find that rich country workers have the greatest advantage in cognitive skills, and in particular in those cognitive skills related to generating new ideas rather than knowledge of existing ideas or facts. Furthermore, these skills closely match the skills used in managerial occupations. We discuss the connection between our results and some theories of what accounts for cross-country variation in GDP per capita, arguing that rich country workers have skills which are well-adapted for the technological environment of rich countries.

References

[1] Arkolakis, C., Ramondo, N., Rodrguez-Clare, A., and Yeaple, S. (2018). Innovation and production in the global economy. *American Economic Review*, 108(8), 2128-73.

[2] Barro, R.J. (1991). Economic Growth in a Cross Section of Countries, *Quarterly Journal of Economics*, 106(2), 407-443.

[3] Barro, R. J., and McCleary, R. (2003). Religion and economic growth, *American Sociological Review.*, 68(5), 760-781.

[4] Bils, M. and P.J. Klenow (2000). Does Schooling Cause Growth?, *American Economic Review*, 90(5), 1160-1183.

[5] Blair, P.Q. and B.W. Chung (2020). A Model of Occupational Licensing and Statistical Discrimination, *AEA Papers and Proceedings*, forthcoming.

[6] Bloom, N., Eifert, B., Mahajan, A., McKenzie, D., and J. Roberts (2013). Does Management Matter? Evidence from India, *Quarterly Journal of Economics*, 128(1), 1-51.

[7] Borjas, G.J. (1987). Self-selection and the earnings of immigrants, *American Economic Review*, Vol. 77, No. 4, pp. 531-553.

[8] Borjas, G.J. (1992). Ethnic Capital and Intergenerational Mobility, *Quarterly Journal of Economics*, 107(1), 123-150.

[9] Bratsberg, B. and D. Terrell (2002). School Quality and Returns to Education of U.S. Immigrants, *Economic Inquiry*, 40(2), 177-198.

[10] Cantrell, J. A. (1992). A comparison of cognitive ability measures in the prediction of achievement in a referred population of college students, *The Ohio State University.*

[11] Caselli, F. (2005). Accounting for cross-country income differences. *Handbook of economic growth*, 1, 679-741.

[12] Chiswick, B.R. (1978). The Effect of Americanization on the Earnings of Foreign-born Men, *Journal of Political Economy*, 86(5), 897-921.

[13] De Philippis, M. and Rossi, F. (2020). Parents, schools and human capital differences across countries. *Journal of the European Economic Association*, forthcoming.

[14] Deming, D. and L.B. Kahn (2018). Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals, *Journal of Labor Economics*, 36(S1), S337-S369.

[15] Department of Homeland Security (2019). Estimates of the Lawful Permanent Resident Population in the United States and the Subpopulation Eligible to Naturalize: 2015-2019. DHS Office of Immigration Statistics.

[16] Department of Homeland Security (2018). Illegal Alien Population Residing in the United States: January 2015. DHS Office of Immigration Statistics.

[17] Department of Homeland Security (2018). Nonimmigrants Residing in the United States: Fiscal Year 2016. DHS Office of Immigration Statistics.

[18] DiNardo, J.E. and J. Pischke (1997). The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too?, *Quarterly Journal of Economics*, 112(1), 291-303.

[19] Dustmann, C. and Glitz, A. (2011). Migration and education. In *Handbook of the Economics of Education*, 4, 327-439. Elsevier.

[20] Dustmann, C. and C. Meghir (2005). Wage, Experience and Seniority, *Review of Economic Studies*, 72(1), 77-108.

[21] Fulford, S.L., Petkov, I., and F. Schiantarelli (2020). Does it matter where you came from? Ancestry composition and economic performance of US counties, 1850-2010. *Journal of Economic Growth*, 25(3), 341-380.

[22] Gardner, H. (1983). Frames of Mind: The Theory of Multiple Intelligences, New York: Basic Books.

[23] Giorcelli, M. (2019). The Long-Term Effects of Management and Technology Transfers, *American Economic Review*, 109(1), 121-152.

[24] Guvenen, F., Kuruscu, B., Tanaka, S. and D. Wiczer (2020). Multidimensional Skill Mismatch, *American Economic Journal: Macroeconomics*, 12(1), 210-44.

[25] Hanushek, E.A. and D.D. Kimko (2000). Schooling, Labor-Force Quality, and the Growth of Nations, *American Economic Review*, 90(5), 1184-1208.

[26] Hanushek, E.A. and L. Woessmann (2008). The Role of Cognitive Skills in Economic Development, *Journal of Economic Literature*, 46(3), 607-668.

[27] Hanushek, E.A. and L. Woessmann (2012). Do Better Schools Lead to More Growth? Cognitive Skills, Economic Outcomes, and Causation, *Journal of Economic Growth*, 17, 267-321.

[28] Heckman, J.J. (2008). Schools, Skills, and Synapses, *Economic Inquiry*, 46(3), 289-324.

[29] Heckman, J.J., Jagelka, T. and Kautz, T. D. (2019). Some contributions of economics to the study of personality (No. w26459). National Bureau of Economic Research.

[30] Hendricks, L. (2002). How Important is Human Capital for Development? Evidence from Immigrant Earnings, *American Economic Review*, 198-219.

[31] Hendricks, L. and T. Schoellman (2018). Human Capital and Development Accounting: New Evidence from Wage Gains at Migration, *Quarterly Journal of Economics*, 133(2), 665-700.

[32] Hidalgo, C. A., and Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the national academy of sciences, 106(26)*, 10570-10575.

[33] Hsieh, C. T. and P.J. Klenow (2009). Misallocation and Manufacturing TFP in India and China. *Quarterly Journal of Economics*, 124(4), 1403-1448.

[34] Hsieh, C. T. and P.J. Klenow (2010). Development accounting. *American Economic Journal: Macroeconomics*, 2(1), 207-23.

[35] Jones, B.F. (2014). The Human Capital Stock: A Generalized Approach, *American Economic Review*, 104(11), 3752-3777.

[36] Jones, C. I., and Romer, P. M. (2010). The new Kaldor facts: ideas, institutions, population, and human capital. *American Economic Journal: Macroeconomics*, 2(1), 224-45.

[37] Kambourov, G. and I. Manovskii (2009). Occupational Specificity of Human Capital, *International Economic Review*, 50(1), 63-115.

[38] Kinsler, J. and R. Pavan (2015). The Specificity of General Human Capital: Evidence from College Major Choice, *Journal of Labor Economics*, 33(4), 933-972.

[39] Kirkeboen, L.J., Leuven, E., Mogstad, M. (2016). Field of Study, Earnings, and Self-Selection. *Quarterly Journal of Economics*, 131(3), 1057-1111.

[40] Klenow, P.J. and A. Rodriguez-Clare (1997). The Neoclassical Revival in Growth Economics: Has It Gone Too Far?, *NBER Macroeconomics Annual 1997*, 12, ed. by Ben S. Bernanke and Julio Rotemberg. Cambridge: MIT Press.

[41] Lagakos, D., Moll, B., Porzio, T., Qian, N., and T. Schoellman (2018a). Life Cycle Wage Growth across Countries, *Journal of Political Economy*, 126(2), 797-849.

[42] Lagakos, D., Moll, B., Porzio, T., Qian, N., and T. Schoellman (2018b). Life-Cycle Human Capital Accumulation across Countries: Lessons from US Immigrants, *Journal of Human Capital*, 12(2), 305-342.

[43] Li, Y., and Rama, M. (2015). Firm dynamics, productivity growth, and job creation in developing countries: The role of micro-and small enterprises. *The World Bank Research Observer*, 30(1), 3-38.

[44] Lise, J., Postel-Vinay, F. (2020). Multidimensional Skills, Sorting, and Human Capital Accumulation. American Economic Review, forthcoming.

[45] Mankiw, N.G., Romer, D., and D.N. Weil (1992). A Contribution to the Empirics of Economic Growth, *Quarterly Journal of Economics*, 107(2), 407-437.

[46] Manuelli, R.E. and A. Seshadri (2014). Human Capital and the Wealth of Nations, *American Economic Review*, 104(9), 2736-2762.

[47] Neal, D. (1995). Industry-Specific Human Capital: Evidence from Displaced Workers, *Journal of Labor Economics*, 13(4), 653-677.

[48] Oreopoulos, P. (2011). Why Do Skilled Immigrants Struggle in the Labor Market? A Field Experiment with Thirteen Thousand Resumes. *American Economic Journal: Economic Policy*, 3(4), 148-171.

[49] Pagano, P. and F. Schivardi (2003). Firm Size Distribution and Growth, *Scandinavian Journal of Economics*, 105(2), 255-274.

[50] Paglin, M., Rufolo, A. M. (1990). Heterogeneous Human Capital, Occupational Choice, and Male-Female Earnings Differences. *Journal of Labor Economics*, 8(1), 123-144.

[51] Patel, K. and F. Vella (2013). Immigrant Networks and Their Implications for Occupational Choice and Wages. *Review of Economics and Statistics*, 95(4), 1249-1277.

[52] Plomin, R. (2019). *Blueprint: How DNA Makes Us Who We Are*, MIT Press.

[53] Poschke, M. (2018). The firm size distribution across countries and skill-biased change in entrepreneurial technology. *American Economic Journal: Macroeconomics*, 10(3), 1-41.

[54] Roy, A.D. (1951). Some Thoughts on the Distribution of Earnings, *Oxford Economic Papers*, 3(2), 135-146.

[55] Ruggles, S., Flood, S., Goeken, R., Grover, J., Meyer, E., Pacas, J. and Sobek, M. (2020). IPUMS USA: Version 10.0 [dataset]. Minneapolis: IPUMS, 2020. https://doi.org/10.18128/D010.V10.0

[56] Schoellman, T. (2010). The Occupations and Human Capital of U.S. Immigrants, *Journal of Human Capital*, 4(1), 1-34.

[57] Schoellman, T. (2012). Education Quality and Development Accounting, *Review of Economic Studies*, 79(1), 388-417.

[58] Schumpeter, J. (1942). Creative destruction. *Capitalism, socialism and democracy*, 825, 82-85.

[59] Slichter, S. (1950). Notes on the Structure of Wages, *Review of Economics and Statistics*, 32, 80-91.

[60] Spearman, C. (1904). "General Intelligence," Objectively Determined and Measured, *American Journal of Psychology*, 15(2), 201-292.

[61] Solow, R.M. (1956). A Contribution to the Theory of Economic Growth, *Quarterly Journal of Economics*, 70(1), 65-94.

[62] Symeonidis, G. (1996). Innovation, Firm Size and Market Structure: Schumpeterian Hypotheses and Some New Themes, OECD working paper No. 161.

[63] Tabellini, G. (2010). Culture and Institutions: Economic Development in the Regions of Europe, *Journal of the European Economic Association*, 8(4), 677-716.

[64] Tybout, J.R. (2000). Manufacturing Firms in Developing Countries: How Well Do They Do, and Why? *Journal of Economic Literature*, 38, 11-44.

[65] Waldinger, R. (1994). The Making of an Immigrant Niche, *International Migration Review*, 28(1), 3-30.

Appendix

A Main results

Table 7: Complete main results

O*NET category	Skill	Coef.	Std.Err.
Skills	Systems Analysis	0.164	(0.015)
Abilities	Fluency of Ideas	0.159	(0.013)
Abilities	Originality	0.158	(0.013)
Skills	Systems Evaluation	0.158	(0.015)
Skills	Complex Problem Solving	0.157	(0.015)
Skills	Active Learning	0.150	(0.016)
Skills	Critical Thinking	0.150	(0.016)
Skills	Reading Comprehension	0.149	(0.016)
WorkStyle	Achievement/Effort	0.147	(0.015)
Skills	Operations Analysis	0.146	(0.011)

Abilities	Written Comprehension	0.143	(0.016)
Knowledge	English Language	0.141	(0.016)
Knowledge	Geography	0.140	(0.012)
WorkStyle	Initiative	0.139	(0.015)
Knowledge	Communications and Media	0.138	(0.016)
Abilities	Written Expression	0.136	(0.017)
Abilities	Deductive Reasoning	0.135	(0.016)
WorkStyle	Analytical Thinking	0.135	(0.016)
Skills	Writing	0.135	(0.017)
Skills	Speaking	0.133	(0.016)
WorkStyle	Persistence	0.131	(0.015)
Abilities	Category Flexibility	0.130	(0.013)
Knowledge	Administration and Management	0.130	(0.012)
Abilities	Speech Clarity	0.129	(0.016)
Knowledge	Economics and Accounting	0.128	(0.014)
WorkStyle	Innovation	0.126	(0.013)
Knowledge	Computers and Electronics	0.125	(0.015)
Skills	Programming	0.124	(0.015)
Abilities	Inductive Reasoning	0.123	(0.017)
Abilities	Mathematical Reasoning	0.122	(0.015)
Skills	Judgment and Decision Making	0.122	(0.014)
Skills	Learning Strategies	0.118	(0.015)
Abilities	Oral Expression	0.117	(0.017)
Knowledge	Mathematics	0.117	(0.013)
Skills	Active Listening	0.116	(0.016)
Knowledge	History and Archeology	0.113	(0.013)
Skills	Management of Personnel Resources	0.112	(0.010)
Abilities	Information Ordering	0.111	(0.012)
Skills	Mathematics	0.107	(0.015)
Abilities	Number Facility	0.106	(0.015)
Abilities	Oral Comprehension	0.105	(0.016)
Abilities	Memorization	0.105	(0.015)
Knowledge	Personnel and Human Resources	0.103	(0.011)
WorkStyle	Leadership	0.103	(0.012)
Skills	Technology Design	0.102	(0.011)
Abilities	Speech Recognition	0.102	(0.014)
Skills	Persuasion	0.100	(0.013)
Skills	Instructing	0.100	(0.015)
Skills	Time Management	0.100	(0.011)
Knowledge	Law and Government	0.098	(0.014)
Skills	Negotiation	0.093	(0.013)
Knowledge	Engineering and Technology	0.086	(0.010)
Skills	Science	0.085	(0.013)

Skills	Monitoring	0.085	(0.013)
Knowledge	Education and Training	0.085	(0.013)
Knowledge	Sales and Marketing	0.082	(0.012)
Skills	Management of Financial Resources	0.081	(0.010)
Knowledge	Design	0.079	(0.010)
Skills	Coordination	0.078	(0.011)
Abilities	Speed of Closure	0.077	(0.013)
Abilities	Flexibility of Closure	0.076	(0.010)
WorkStyle	Integrity	0.069	(0.016)
Knowledge	Clerical	0.068	(0.011)
WorkStyle	Adaptability/Flexibility	0.065	(0.015)
Skills	Management of Material Resources	0.064	(0.008)
Abilities	Near Vision	0.060	(0.009)
Abilities	Problem Sensitivity	0.056	(0.014)
WorkStyle	Attention to Detail	0.049	(0.011)
Knowledge	Fine Arts	0.048	(0.008)
Knowledge	Physics	0.048	(0.010)
WorkStyle	Independence	0.046	(0.012)
Skills	Social Perceptiveness	0.044	(0.016)
Knowledge	Sociology and Anthropology	0.043	(0.017)
Knowledge	Biology	0.038	(0.010)
Abilities	Selective Attention	0.037	(0.008)
Knowledge	Building and Construction	0.034	(0.011)
Abilities	Visualization	0.032	(0.010)
WorkStyle	Dependability	0.028	(0.013)
Knowledge	Telecommunications	0.027	(0.012)
Knowledge	Production and Processing	0.024	(0.014)
WorkStyle	Cooperation	0.019	(0.014)
Knowledge	Philosophy and Theology	0.017	(0.014)
Knowledge	Psychology	0.013	(0.016)
WorkStyle	Stress Tolerance	0.009	(0.015)
Abilities	Time Sharing	0.008	(0.009)
Skills	Service Orientation	-0.006	(0.015)
Skills	Installation	-0.008	(0.009)
Knowledge	Foreign Language	-0.011	(0.008)
Knowledge	Customer and Personal Service	-0.011	(0.012)
Abilities	Perceptual Speed	-0.012	(0.009)
Knowledge	Chemistry	-0.016	(0.010)
Abilities	Far Vision	-0.016	(0.009)
Knowledge	Mechanical	-0.022	(0.013)
WorkStyle	Social Orientation	-0.024	(0.014)
Knowledge	Transportation	-0.027	(0.010)
Knowledge	Food Production	-0.032	(0.008)

WorkStyle	Self Control	-0.033	(0.014)
Skills	Equipment Selection	-0.035	(0.013)
Knowledge	Therapy and Counseling	-0.035	(0.017)
WorkStyle	Concern for Others	-0.037	(0.015)
Skills	Repairing	-0.047	(0.012)
Skills	Quality Control Analysis	-0.048	(0.013)
Skills	Equipment Maintenance	-0.048	(0.012)
Abilities	Glare Sensitivity	-0.051	(0.012)
Abilities	Peripheral Vision	-0.051	(0.011)
Knowledge	Medicine and Dentistry	-0.053	(0.016)
Abilities	Night Vision	-0.053	(0.011)
Abilities	Spatial Orientation	-0.055	(0.011)
Abilities	Dynamic Flexibility	-0.055	(0.013)
Abilities	Sound Localization	-0.055	(0.011)
Knowledge	Public Safety and Security	-0.057	(0.012)
Abilities	Visual Color Discrimination	-0.058	(0.012)
Abilities	Auditory Attention	-0.067	(0.009)
Skills	Operation Monitoring	-0.068	(0.012)
Abilities	Hearing Sensitivity	-0.084	(0.009)
Skills	Troubleshooting	-0.084	(0.012)
Abilities	Wrist-Finger Speed	-0.085	(0.014)
Skills	Operation and Control	-0.089	(0.013)
Abilities	Depth Perception	-0.093	(0.013)
Abilities	Rate Control	-0.096	(0.015)
Abilities	Control Precision	-0.106	(0.015)
Abilities	Explosive Strength	-0.116	(0.014)
Abilities	Finger Dexterity	-0.117	(0.015)
Abilities	Reaction Time	-0.119	(0.013)
Abilities	Gross Body Equilibrium	-0.122	(0.014)
Abilities	Response Orientation	-0.122	(0.013)
Abilities	Multilimb Coordination	-0.125	(0.016)
Abilities	Dynamic Strength	-0.126	(0.015)
Abilities	Speed of Limb Movement	-0.127	(0.015)
Abilities	Arm-Hand Steadiness	-0.133	(0.016)
Abilities	Manual Dexterity	-0.134	(0.017)
Abilities	Gross Body Coordination	-0.137	(0.015)
Abilities	Extent Flexibility	-0.137	(0.016)
Abilities	Trunk Strength	-0.141	(0.015)
Abilities	Stamina	-0.144	(0.016)
Abilities	Static Strength	-0.150	(0.016)

Note.- List of all coefficients in regressions of income-conditional skill usage (in standard deviations) on log of GDP per capita (in standard deviations), controlling for survey year fixed effects. $N = 2,212$. Robust standard errors clustered at the country level in parentheses.

B Results from non-randomness robustness checks

This appendix reports results from robustness checks related to the fact that immigrants to the United States are not a random sample of people from their origin country.

The full set of results from the immigration rate robustness check (estimates of ρ^s) are given in Table 8. The full results for the young immigrants robustness check (estimates of $\widetilde{\beta}^s$) are in Table 9. The full set of results for Brazil are in Appendix C, Table 11.

Table 8: Immigration rate robustness check

O*NET category	Skill	Coef.	Std.Err.
Knowledge	Engineering and Technology	4.713	(0.975)
Knowledge	Physics	4.489	(1.132)
Knowledge	Production and Processing	4.334	(1.145)
Knowledge	Design	3.952	(0.921)
Knowledge	Geography	3.164	(1.200)
Knowledge	Chemistry	3.058	(0.880)
Knowledge	Mechanical	3.021	(1.519)
Knowledge	Administration and Management	2.924	(1.207)
Skills	Systems Analysis	2.490	(1.498)
Knowledge	Mathematics	2.397	(1.078)
WorkStyle	Achievement/Effort	2.250	(1.697)
Skills	Equipment Selection	2.238	(1.680)
Skills	Operation and Control	2.214	(0.988)
Knowledge	Building and Construction	2.158	(1.383)
Abilities	Visualization	2.140	(1.017)
Abilities	Dynamic Flexibility	2.137	(1.187)
Skills	Operations Analysis	2.123	(1.514)
Knowledge	Economics and Accounting	2.075	(1.327)
Skills	Technology Design	1.919	(0.947)
Skills	Operation Monitoring	1.901	(1.259)
Abilities	Rate Control	1.840	(1.360)
Knowledge	Sales and Marketing	1.834	(1.050)
Skills	Quality Control Analysis	1.787	(1.007)
Skills	Science	1.721	(1.433)
Skills	Systems Evaluation	1.681	(1.449)
Skills	Programming	1.614	(1.330)
Skills	Equipment Maintenance	1.586	(1.910)

WorkStyle	Innovation	1.570	(1.174)
Knowledge	History and Archeology	1.487	(1.948)
Abilities	Control Precision	1.426	(1.448)
Skills	Troubleshooting	1.422	(1.759)
Skills	Repairing	1.317	(2.053)
Abilities	Glare Sensitivity	1.311	(1.382)
WorkStyle	Analytical Thinking	1.273	(1.539)
Skills	Mathematics	1.250	(1.394)
Abilities	Depth Perception	1.207	(1.474)
Abilities	Wrist-Finger Speed	1.204	(0.935)
Abilities	Mathematical Reasoning	1.147	(1.300)
Skills	Management of Financial Resources	1.122	(1.098)
Abilities	Spatial Orientation	0.875	(1.158)
Abilities	Peripheral Vision	0.841	(1.128)
Abilities	Number Facility	0.777	(1.186)
Knowledge	Personnel and Human Resources	0.772	(1.314)
Abilities	Category Flexibility	0.760	(1.927)
Knowledge	Transportation	0.755	(1.037)
Knowledge	Food Production	0.716	(0.972)
Skills	Management of Personnel Resources	0.672	(1.172)
Abilities	Night Vision	0.596	(1.326)
Abilities	Multilimb Coordination	0.596	(1.586)
Skills	Management of Material Resources	0.589	(1.073)
Knowledge	Fine Arts	0.579	(1.349)
Abilities	Fluency of Ideas	0.576	(1.182)
Abilities	Originality	0.565	(1.244)
Abilities	Manual Dexterity	0.482	(1.605)
Abilities	Speed of Limb Movement	0.395	(1.437)
WorkStyle	Initiative	0.345	(1.154)
Skills	Complex Problem Solving	0.341	(1.410)
Abilities	Sound Localization	0.339	(1.280)
Knowledge	Biology	0.323	(0.923)
Abilities	Reaction Time	0.290	(1.144)
Abilities	Dynamic Strength	0.234	(1.628)
WorkStyle	Leadership	0.213	(1.389)
Skills	Installation	0.059	(2.143)
Abilities	Visual Color Discrimination	-0.015	(1.171)
Abilities	Arm-Hand Steadiness	-0.030	(1.690)
Knowledge	Communications and Media	-0.079	(1.684)
WorkStyle	Independence	-0.119	(1.250)
Skills	Critical Thinking	-0.188	(1.570)
Abilities	Extent Flexibility	-0.233	(1.570)
WorkStyle	Persistence	-0.401	(1.467)

Abilities	Trunk Strength	-0.419	(1.528)
Skills	Judgment and Decision Making	-0.447	(1.261)
Skills	Time Management	-0.461	(1.160)
Abilities	Far Vision	-0.523	(0.924)
Abilities	Response Orientation	-0.588	(1.265)
Abilities	Deductive Reasoning	-0.604	(1.481)
Knowledge	Computers and Electronics	-0.615	(1.558)
Abilities	Stamina	-0.758	(1.393)
Abilities	Finger Dexterity	-0.800	(1.860)
Abilities	Static Strength	-0.825	(1.540)
Skills	Active Learning	-0.867	(1.566)
Abilities	Flexibility of Closure	-0.880	(1.143)
Abilities	Inductive Reasoning	-0.903	(1.754)
Knowledge	Law and Government	-0.931	(1.789)
Abilities	Information Ordering	-1.060	(1.290)
Knowledge	Education and Training	-1.115	(1.412)
Abilities	Gross Body Coordination	-1.154	(1.456)
Abilities	Near Vision	-1.167	(1.147)
Skills	Instructing	-1.319	(1.393)
Skills	Learning Strategies	-1.431	(1.586)
Knowledge	Foreign Language	-1.438	(1.153)
Abilities	Hearing Sensitivity	-1.465	(1.038)
Skills	Persuasion	-1.556	(1.036)
Skills	Reading Comprehension	-1.587	(1.482)
Skills	Monitoring	-1.600	(1.619)
Abilities	Written Comprehension	-1.652	(1.518)
Skills	Writing	-1.699	(1.719)
Skills	Negotiation	-1.882	(0.975)
Abilities	Speech Clarity	-1.885	(1.311)
Skills	Speaking	-1.916	(1.352)
Abilities	Auditory Attention	-1.961	(0.820)
Skills	Coordination	-1.966	(1.004)
Knowledge	English Language	-1.981	(1.283)
Knowledge	Public Safety and Security	-2.007	(1.153)
Abilities	Written Expression	-2.008	(1.719)
Abilities	Gross Body Equilibrium	-2.018	(1.355)
Abilities	Oral Expression	-2.200	(1.527)
Abilities	Memorization	-2.203	(1.233)
Abilities	Selective Attention	-2.521	(1.128)
Abilities	Speed of Closure	-2.709	(1.186)
Abilities	Problem Sensitivity	-2.723	(1.190)
Knowledge	Telecommunications	-2.727	(1.098)
WorkStyle	Attention to Detail	-2.813	(1.082)

Abilities	Oral Comprehension	-3.020	(1.393)
Abilities	Perceptual Speed	-3.041	(0.816)
Abilities	Speech Recognition	-3.061	(1.061)
Skills	Active Listening	-3.081	(1.126)
Abilities	Explosive Strength	-3.383	(1.187)
Knowledge	Clerical	-3.409	(0.928)
Knowledge	Sociology and Anthropology	-3.442	(1.257)
WorkStyle	Integrity	-3.488	(1.172)
WorkStyle	Adaptability/Flexibility	-3.882	(0.984)
Knowledge	Philosophy and Theology	-4.271	(1.289)
Knowledge	Customer and Personal Service	-4.463	(1.150)
Skills	Social Perceptiveness	-4.602	(1.059)
Knowledge	Medicine and Dentistry	-4.641	(1.260)
Abilities	Time Sharing	-4.698	(1.324)
Knowledge	Psychology	-5.150	(1.086)
WorkStyle	Stress Tolerance	-5.341	(1.075)
Skills	Service Orientation	-5.861	(0.912)
Knowledge	Therapy and Counseling	-5.950	(0.981)
WorkStyle	Dependability	-5.963	(1.083)
WorkStyle	Social Orientation	-5.994	(1.269)
WorkStyle	Self Control	-6.346	(1.325)
WorkStyle	Concern for Others	-6.411	(1.351)
WorkStyle	Cooperation	-6.412	(0.970)

Note.- List of estimates of ρ^s. $N = 2,206$. Robust standard errors clustered at the country level in parentheses.

Table 9: Young immigrants robustness check

Type	ElementName	Coef.	Std.Err.
Knowledge	Economics and Accounting	0.029	(0.008)
Knowledge	Building and Construction	0.024	(0.008)
Knowledge	Mathematics	0.023	(0.009)
Knowledge	Production and Processing	0.023	(0.008)
Abilities	Dynamic Flexibility	0.023	(0.010)
Knowledge	Mechanical	0.022	(0.009)
Knowledge	Geography	0.021	(0.008)
Knowledge	Sales and Marketing	0.018	(0.010)
Knowledge	Administration and Management	0.017	(0.008)
Knowledge	Design	0.017	(0.008)
Knowledge	Engineering and Technology	0.016	(0.008)
Knowledge	History and Archeology	0.014	(0.010)
WorkStyle	Initiative	0.014	(0.008)
Skills	Operations Analysis	0.014	(0.009)

WorkStyle	Achievement/Effort	0.013	(0.009)
Abilities	Glare Sensitivity	0.013	(0.012)
Skills	Mathematics	0.013	(0.010)
Knowledge	Physics	0.012	(0.006)
Abilities	Night Vision	0.011	(0.012)
Abilities	Sound Localization	0.011	(0.011)
Abilities	Spatial Orientation	0.011	(0.011)
Skills	Speaking	0.010	(0.009)
Knowledge	Clerical	0.010	(0.008)
Skills	Installation	0.010	(0.007)
Abilities	Speech Clarity	0.010	(0.009)
Abilities	Mathematical Reasoning	0.010	(0.010)
WorkStyle	Attention to Detail	0.010	(0.011)
Abilities	Peripheral Vision	0.009	(0.012)
Knowledge	Transportation	0.009	(0.014)
WorkStyle	Leadership	0.009	(0.008)
WorkStyle	Persistence	0.009	(0.009)
Abilities	Speech Recognition	0.008	(0.009)
Abilities	Number Facility	0.008	(0.011)
Skills	Management of Financial Resources	0.007	(0.010)
Skills	Repairing	0.007	(0.009)
Skills	Management of Personnel Resources	0.006	(0.009)
Abilities	Written Comprehension	0.006	(0.010)
Skills	Programming	0.006	(0.001)
Abilities	Near Vision	0.006	(0.010)
Skills	Equipment Maintenance	0.006	(0.010)
Abilities	Perceptual Speed	0.006	(0.009)
Knowledge	English Language	0.006	(0.008)
Skills	Critical Thinking	0.005	(0.011)
Abilities	Flexibility of Closure	0.004	(0.009)
Knowledge	Law and Government	0.004	(0.009)
WorkStyle	Analytical Thinking	0.004	(0.011)
Abilities	Auditory Attention	0.004	(0.010)
Abilities	Category Flexibility	0.004	(0.010)
Skills	Systems Analysis	0.004	(0.011)
Abilities	Visualization	0.004	(0.009)
Knowledge	Personnel and Human Resources	0.004	(0.010)
Abilities	Speed of Limb Movement	0.004	(0.010)
Knowledge	Food Production	0.004	(0.007)
Abilities	Selective Attention	0.003	(0.009)
Abilities	Deductive Reasoning	0.003	(0.011)
Skills	Equipment Selection	0.003	(0.008)
Abilities	Wrist-Finger Speed	0.003	(0.009)

Skills	Reading Comprehension	0.003	(0.010)
Skills	Systems Evaluation	0.002	(0.011)
Abilities	Depth Perception	0.002	(0.010)
Abilities	Dynamic Strength	0.002	(0.011)
Abilities	Rate Control	0.002	(0.010)
WorkStyle	Dependability	0.002	(0.009)
Skills	Coordination	0.002	(0.009)
Skills	Negotiation	0.002	(0.010)
WorkStyle	Innovation	0.002	(0.009)
Abilities	Multilimb Coordination	0.002	(0.010)
Skills	Time Management	0.001	(0.010)
Abilities	Information Ordering	0.001	(0.010)
Abilities	Speed of Closure	0.001	(0.010)
Knowledge	Communications and Media	0.001	(0.010)
Skills	Active Learning	0.001	(0.011)
Skills	Persuasion	0.001	(0.010)
Skills	Quality Control Analysis	0.001	(0.009)
Knowledge	Customer and Personal Service	0.001	(0.008)
Skills	Active Listening	0.001	(0.011)
Abilities	Oral Expression	0.000	(0.010)
Knowledge	Computers and Electronics	0.000	(0.009)
Abilities	Far Vision	0.000	(0.011)
Skills	Complex Problem Solving	0.000	(0.011)
WorkStyle	Integrity	0.000	(0.009)
Skills	Operation and Control	0.000	(0.011)
Skills	Management of Material Resources	0.000	(0.010)
Abilities	Extent Flexibility	0.000	(0.010)
Abilities	Hearing Sensitivity	-0.001	(0.009)
Abilities	Originality	-0.001	(0.010)
Knowledge	Education and Training	-0.001	(0.010)
Skills	Operation Monitoring	-0.001	(0.011)
Skills	Judgment and Decision Making	-0.001	(0.011)
Abilities	Inductive Reasoning	-0.002	(0.012)
Abilities	Control Precision	-0.002	(0.010)
Abilities	Written Expression	-0.002	(0.010)
Skills	Technology Design	-0.002	(0.008)
Knowledge	Foreign Language	-0.002	(0.008)
Abilities	Gross Body Equilibrium	-0.003	(0.011)
Abilities	Reaction Time	-0.004	(0.011)
Abilities	Manual Dexterity	-0.004	(0.009)
WorkStyle	Independence	-0.004	(0.007)
Abilities	Time Sharing	-0.004	(0.010)
Skills	Learning Strategies	-0.004	(0.011)

Abilities	Finger Dexterity	-0.004	(0.009)
Skills	Instructing	-0.004	(0.009)
Abilities	Trunk Strength	-0.004	(0.010)
Knowledge	Fine Arts	-0.004	(0.009)
Abilities	Stamina	-0.005	(0.011)
Abilities	Visual Color Discrimination	-0.005	(0.009)
Abilities	Oral Comprehension	-0.005	(0.010)
Abilities	Static Strength	-0.005	(0.010)
Skills	Writing	-0.006	(0.011)
Abilities	Memorization	-0.006	(0.010)
Abilities	Fluency of Ideas	-0.007	(0.010)
Abilities	Arm-Hand Steadiness	-0.007	(0.010)
Skills	Monitoring	-0.007	(0.010)
Skills	Troubleshooting	-0.007	(0.010)
Abilities	Gross Body Coordination	-0.008	(0.011)
Abilities	Response Orientation	-0.008	(0.010)
Knowledge	Telecommunications	-0.008	(0.011)
Skills	Social Perceptiveness	-0.008	(0.011)
Knowledge	Biology	-0.008	(0.010)
WorkStyle	Adaptability/Flexibility	-0.009	(0.008)
Skills	Science	-0.010	(0.010)
Knowledge	Chemistry	-0.010	(0.007)
WorkStyle	Stress Tolerance	-0.012	(0.009)
WorkStyle	Cooperation	-0.012	(0.009)
Abilities	Explosive Strength	-0.013	(0.012)
Abilities	Problem Sensitivity	-0.013	(0.011)
Skills	Service Orientation	-0.015	(0.010)
Knowledge	Public Safety and Security	-0.015	(0.014)
WorkStyle	Social Orientation	-0.016	(0.010)
Knowledge	Philosophy and Theology	-0.016	(0.012)
Knowledge	Psychology	-0.017	(0.012)
Knowledge	Sociology and Anthropology	-0.020	(0.012)
WorkStyle	Self Control	-0.020	(0.011)
WorkStyle	Concern for Others	-0.021	(0.011)
Knowledge	Medicine and Dentistry	-0.027	(0.011)
Knowledge	Therapy and Counseling	-0.029	(0.013)

Note.- List of estimates of $\widetilde{\beta}^s$. $N = 125$. Robust standard errors in parentheses.

We now ask whether these robustness checks suggest that our main results are sensitive to the non-randomness of immigration. We assess this in turn for each of our three main findings: (i) that rich country workers have a particular specialization in ideas relative to knowledge, (ii) that the skills of rich country workers closely resemble the skills of higher-earning individuals in general, and (iii) that the skills

Table 10: Non-randomness in ideas versus knowledge skills

Skill	Immigration rate Coef.	Std.Err.	Young immigrants Coef.	Std.Err.
Ideas				
Systems Analysis	2.490	(1.498)	0.004	(0.011)
Fluency of Ideas	0.576	(1.182)	-0.007	(0.010)
Originality	0.565	(1.244)	-0.001	(0.010)
Systems Evaluation	1.681	(1.449)	0.002	(0.011)
Complex Problem Solving	0.341	(1.410)	0.000	(0.011)
Active Learning	-0.867	(1.566)	0.001	(0.011)
Critical Thinking	-0.188	(1.570)	0.005	(0.011)
Operations Analysis	2.123	(1.514)	0.014	(0.009)
Average	0.840		0.002	
Knowledge				
Knowledge of Geography	3.164	(1.200)	0.021	(0.008)
Knowledge of Mathematics	2.397	(1.078)	0.023	(0.009)
Knowledge of Engineering and Technology	4.713	(0.975)	0.016	(0.008)
Knowledge of Physics	4.489	(1.132)	0.012	(0.006)
Knowledge of Biology	0.323	(0.923)	-0.008	(0.010)
Knowledge of Psychology	-5.150	(1.086)	-0.017	(0.012)
Knowledge of Chemistry	3.058	(0.880)	-0.010	(0.007)
Knowledge of Medicine and Dentistry	-4.641	(1.260)	-0.027	(0.011)
Average	1.044		0.001	

Note.- List of coefficients for skills categorized as "ideas" or "knowledge" skills, for robustness checks using immigration rate and young immigrants to measure non-randomness in immigration. Robust standard errors (clustered at the country level for immigration rate estimates) in parentheses.

of rich country workers resemble the skills of people in managerial occupations.

Specialization in ideas vs. knowledge Table 10 below highlights the estimated coefficients for non-random selection for skills which in Section 3 we described as being related to the production of ideas, as well as for variables we described as being knowledge-related.

Both categories show somewhat positive coefficients on average (though not consistently across all skills), suggesting that the main estimates β^s could be biased upwards due to non-randomness of immigration for both ideas and knowledge skills.

However, the results do not suggest a *differential* bias that would inflate ideas-related coefficients relative to knowledge-related coefficients.

Alignment with skills of high individual earners In Section 3, we found a close alignment between the skills of rich country workers and the skills of high-earning individuals. Non-random immigration could either increase or decrease the strength of this relationship.

The correlations of our two estimates of non-randomness, $\widehat{\rho}^s$ and $\widehat{\widehat{\beta}}^s$, with the estimated still of high-earning individuals, $\widehat{\alpha}^s$, are .01 and .22, respectively. This suggests that our results are likely somewhat biased in the direction of α^s.

However, it does not necessarily mean that the *correlation* between β^s and α^s is overstated. In general, for any η^s which is drawn independent of β^s and α^s, $\beta^s + \eta^s$ would be less correlated with α^s than β^s is. Introducing some correlation between η^s and α^s does not change this conclusion if that correlation is sufficiently small and the correlation between β^s and α^s is sufficiently strong – e.g., if β^s and α^s have correlation of 1, then $\beta^s+\eta^s$ is less correlated with α^s whenever η^s is not also perfectly correlated with α^s.

We do not observe the exact bias due to non-randomness, and therefore cannot draw strong conclusions about its effect on the correlation between β^s and α^s. However, given the correlation between $\widehat{\beta}^s$ and $\widehat{\alpha}^s$ is above .9, while the correlation between $\widehat{\alpha}^s$ and our measures of non-randomness is far smaller, it is clearly quite possible that our results might even *under*estimate the correlation which would prevail if immigrants were chosen at random from the origin country population.

Alignment with managerial skill We can also ask whether our finding that managerial skills are differentially produced in rich countries is sensitive to non-randomness of immigration. As a reminder, fitting our main results with the best-fit occupation yielded the best match to Logisticians, with an r-squared of .66.

Following the procedure in Section 3, we find the best fit to our immigration rates coefficients using the same occupation by regressing $\widehat{\rho}^s$ on Occ_j^s for j, Logisticians the constant from the regression. This regression gives an r-squared of .02 and $\widehat{\lambda}$ of .41 (standard error .23). The magnitude of $\widehat{\lambda}$ does not have a clear interpretation, since $\widehat{\rho}^s$ does not have easily interpretable units, but the positive sign can be interpreted as suggesting that our main results are biased in favor of managerial skills – though we cannot statistically reject λ of 0.

Fitting our results for immigrants at the ages of 0-2 in the same way gives an r-squared of .12 and $\widehat{\lambda}$ of .004 (standard error .001). The positive sign and non-trivial r-squared suggest that the bias induced by non-random immigration might somewhat overstate differences in managerial skills – though, again, some appearance of overstatement might also be expected due to cultural transmission from parents to children. However, the *magnitude* of alignment can now be directly compared with the main results, and is far smaller than for the main results – with λ_j of .004 instead of .085 in our main results.

Combined, these tests suggest the qualitative conclusions that (i) our main results may somewhat overstate the extent of differences in managerial skill, but (ii) this overstatement is unlikely to be a first-order important explanation for our main results.

As in the discussion above of the alignment between β^s and α^s, one object of interest is the r-squared of the fit with logisticians' skills, which indicates how well our main results are described as "the skills of logisticians" – but, because we do not observe an exact measure of bias, we cannot be confident whether non-randomness serves to increase this r-squared. However, the much weaker alignment of logisticians' skills with the non-randomness estimates than with the main results suggests that the r-squared might well be underestimated.

Evidence about specialization In Section 5, we offer evidence that workers from rich countries are more specialized in their strengths, using two measures of lopsidedness: sorting into lopsided occupations, and within-country variance of skills.

For the within-country variance of skills, using the sample of young immigrants instead of recent immigrants gives a coefficient of .009 with a standard error of .007. Using within-country variance var_c as the skill s in the immigration rate measure of non-randomness, the estimated coefficient of interest, $\widehat{\rho^s}$, is estimated to be $-.89$, with a standard error of 1.06. Neither of these results is significant, and combined, they do not suggest that non-randomness of immigration accounts for rich countries' greater within-country variance of skills.

For the lopsidedness measure, the young immigrants measure gives a coefficient of $-.001$ with a standard error of .006. Meanwhile, the coefficient of interest in the immigration rate measure is -1.36 with a standard error of 1.25. Neither of these coefficients is statistically significant.

In short, we do not find evidence that non-randomness drives our results about greater specialization among rich country workers.

C Results from Brazilian data

As a robustness check described in Section 4, we also run our main results using the 2010 long form Brazilian census. The specification is lightly modified from our ACS specification because we are working with only a single wave of data (prior years of the Brazilian census used only two-digit occupation codes, which is not detailed enough to reliably match to O*NET measures).

We only include individuals who are employed, since these are the ones with occupation information and income. For this subsample we have the birthplace and occupation information.

As in our main results, for each country of birth, we construct the average income-conditional skill, measured in units of standard deviations above or below the average within the same income decile (i.e., a separate mean and standard deviation of each skill is calculated for each income decile to produce this measure).

Our regressions use individuals who immigrated within the five years before the census. Moreover, we want to concentrate on people of working age, so we estimate only including those with age between 25 and 60. We aggregate observations to the country level by averaging, and only use countries which have at least 20 people on the dataset. In the Brazilian data, this results in a sample consisting of only 17 countries.

Results for our main analysis and analysis for young immigrants (ages 0-2 at the time of immigration), performed on Brazilian data, are shown in Table 11. Note that these results are considerably more noisy than the estimates from US data; e.g., most coefficient estimates are not statistically significant, in contrast with the US estimates where the great majority of coefficients are statistically significant.

Table 11: Brazil data robustness check

		Main results		Young immigrants	
O*NET category	Skill	Coef.	Std.Err.	Coef.	Std.Err.
Knowledge	History and Archeology	0.265	(0.124)	0.093	(0.076)
Abilities	Memorization	0.264	(0.068)	0.129	(0.091)
Knowledge	Fine Arts	0.260	(0.058)	0.103	(0.087)
Knowledge	Geography	0.254	(0.100)	0.141	(0.041)
Abilities	Fluency of Ideas	0.242	(0.089)	0.084	(0.090)
WorkStyle	Innovation	0.239	(0.048)	0.095	(0.063)
Abilities	Originality	0.233	(0.097)	0.089	(0.104)
Knowledge	English Language	0.228	(0.100)	0.062	(0.096)
Knowledge	Communications and Media	0.207	(0.109)	0.117	(0.078)
Knowledge	Education and Training	0.204	(0.094)	0.046	(0.072)
Knowledge	Sociology and Anthropology	0.202	(0.114)	0.164	(0.108)
Knowledge	Philosophy and Theology	0.199	(0.108)	0.104	(0.103)
Skills	Instructing	0.198	(0.092)	0.046	(0.074)
WorkStyle	Adaptability/Flexibility	0.191	(0.090)	0.100	(0.096)
Skills	Learning Strategies	0.189	(0.086)	0.068	(0.085)
Skills	Technology Design	0.189	(0.118)	0.000	(0.073)
Abilities	Speed of Closure	0.187	(0.074)	0.026	(0.096)
WorkStyle	Cooperation	0.186	(0.081)	0.118	(0.077)
WorkStyle	Integrity	0.181	(0.081)	0.030	(0.118)
Knowledge	Foreign Language	0.181	(0.084)	-0.044	(0.040)
WorkStyle	Dependability	0.177	(0.076)	-0.008	(0.076)
WorkStyle	Initiative	0.174	(0.109)	0.013	(0.084)
Skills	Mathematics	0.174	(0.060)	0.047	(0.063)
Skills	Speaking	0.168	(0.127)	0.043	(0.076)
Abilities	Number Facility	0.164	(0.065)	0.014	(0.066)
WorkStyle	Analytical Thinking	0.162	(0.084)	0.003	(0.082)
Abilities	Speech Clarity	0.161	(0.118)	0.050	(0.074)
Skills	Writing	0.160	(0.100)	0.144	(0.100)

Skills	Active Learning	0.159	(0.092)	0.038	(0.083)
Abilities	Oral Expression	0.156	(0.092)	0.110	(0.083)
WorkStyle	Persistence	0.155	(0.069)	0.018	(0.111)
WorkStyle	Leadership	0.154	(0.102)	-0.028	(0.053)
Abilities	Mathematical Reasoning	0.149	(0.072)	0.017	(0.069)
Knowledge	Design	0.148	(0.093)	-0.018	(0.044)
Skills	Systems Analysis	0.148	(0.074)	0.102	(0.093)
Skills	Programming	0.146	(0.080)	0.138	(0.095)
Abilities	Written Expression	0.146	(0.108)	0.086	(0.079)
Skills	Systems Evaluation	0.144	(0.066)	0.099	(0.086)
Skills	Reading Comprehension	0.143	(0.086)	0.089	(0.092)
Abilities	Inductive Reasoning	0.140	(0.059)	0.075	(0.104)
Knowledge	Computers and Electronics	0.140	(0.101)	0.155	(0.091)
Abilities	Oral Comprehension	0.138	(0.098)	0.093	(0.085)
Abilities	Written Comprehension	0.134	(0.082)	0.108	(0.080)
Skills	Active Listening	0.134	(0.091)	0.082	(0.093)
Abilities	Category Flexibility	0.131	(0.067)	0.140	(0.065)
Skills	Service Orientation	0.129	(0.128)	0.003	(0.067)
Abilities	Time Sharing	0.127	(0.094)	0.041	(0.052)
Knowledge	Psychology	0.125	(0.084)	0.104	(0.126)
WorkStyle	Social Orientation	0.124	(0.086)	0.033	(0.080)
Abilities	Speech Recognition	0.123	(0.119)	0.051	(0.072)
WorkStyle	Stress Tolerance	0.122	(0.039)	0.011	(0.072)
Knowledge	Mathematics	0.119	(0.095)	-0.068	(0.045)
Skills	Critical Thinking	0.118	(0.073)	0.069	(0.089)
WorkStyle	Self Control	0.117	(0.069)	0.034	(0.070)
Knowledge	Engineering and Technology	0.114	(0.101)	0.003	(0.048)
Skills	Persuasion	0.104	(0.122)	0.002	(0.063)
Knowledge	Food Production	0.103	(0.064)	0.065	(0.071)
Knowledge	Therapy and Counseling	0.098	(0.090)	0.107	(0.131)
Abilities	Deductive Reasoning	0.098	(0.056)	0.079	(0.089)
Skills	Negotiation	0.098	(0.112)	-0.003	(0.054)
Abilities	Auditory Attention	0.096	(0.069)	-0.007	(0.067)
Abilities	Selective Attention	0.089	(0.047)	-0.034	(0.096)
Abilities	Near Vision	0.088	(0.065)	0.073	(0.060)
Knowledge	Law and Government	0.088	(0.092)	-0.023	(0.051)
Skills	Social Perceptiveness	0.085	(0.112)	0.035	(0.081)
WorkStyle	Concern for Others	0.084	(0.076)	0.033	(0.091)
Skills	Management of Personnel Resources	0.083	(0.082)	0.025	(0.045)
Knowledge	Clerical	0.081	(0.112)	0.038	(0.072)
WorkStyle	Achievement/Effort	0.080	(0.083)	0.004	(0.108)
Skills	Time Management	0.075	(0.068)	0.020	(0.043)
Abilities	Problem Sensitivity	0.074	(0.064)	0.016	(0.085)

Knowledge	Transportation	0.069	(0.080)	0.054	(0.083)
Skills	Coordination	0.066	(0.114)	0.013	(0.043)
Abilities	Information Ordering	0.064	(0.054)	0.062	(0.068)
Skills	Judgment and Decision Making	0.063	(0.058)	0.107	(0.084)
WorkStyle	Attention to Detail	0.062	(0.083)	-0.016	(0.057)
Abilities	Far Vision	0.058	(0.055)	0.046	(0.049)
Knowledge	Physics	0.057	(0.079)	-0.020	(0.047)
Knowledge	Customer and Personal Service	0.055	(0.126)	0.018	(0.054)
Skills	Complex Problem Solving	0.053	(0.055)	0.086	(0.081)
Knowledge	Personnel and Human Resources	0.050	(0.107)	-0.006	(0.045)
Knowledge	Telecommunications	0.049	(0.130)	0.062	(0.076)
Knowledge	Economics and Accounting	0.047	(0.124)	-0.088	(0.042)
Abilities	Flexibility of Closure	0.046	(0.066)	0.074	(0.078)
Knowledge	Building and Construction	0.044	(0.086)	-0.120	(0.049)
Skills	Installation	0.044	(0.062)	-0.124	(0.046)
Knowledge	Administration and Management	0.042	(0.123)	-0.001	(0.048)
Knowledge	Sales and Marketing	0.042	(0.125)	0.028	(0.047)
WorkStyle	Independence	0.040	(0.081)	0.015	(0.100)
Skills	Science	0.031	(0.054)	0.076	(0.098)
Skills	Equipment Selection	0.028	(0.073)	-0.029	(0.063)
Abilities	Perceptual Speed	0.024	(0.094)	0.047	(0.031)
Skills	Management of Material Resources	0.023	(0.096)	0.001	(0.067)
Skills	Operations Analysis	0.016	(0.068)	0.034	(0.042)
Knowledge	Public Safety and Security	0.015	(0.090)	-0.049	(0.046)
Abilities	Hearing Sensitivity	0.014	(0.071)	-0.014	(0.056)
Skills	Management of Financial Resources	0.009	(0.087)	0.021	(0.063)
Skills	Monitoring	0.004	(0.050)	0.033	(0.061)
Knowledge	Chemistry	0.000	(0.083)	-0.072	(0.057)
Abilities	Visualization	-0.002	(0.092)	0.072	(0.046)
Skills	Repairing	-0.004	(0.071)	-0.027	(0.008)
Abilities	Sound Localization	-0.009	(0.089)	-0.014	(0.095)
Skills	Equipment Maintenance	-0.019	(0.074)	-0.015	(0.083)
Abilities	Glare Sensitivity	-0.023	(0.090)	-0.041	(0.095)
Abilities	Spatial Orientation	-0.024	(0.084)	-0.020	(0.104)
Knowledge	Biology	-0.024	(0.052)	0.101	(0.075)
Abilities	Dynamic Flexibility	-0.026	(0.065)	-0.118	(0.062)
Abilities	Trunk Strength	-0.029	(0.075)	-0.187	(0.097)
Knowledge	Mechanical	-0.030	(0.079)	-0.087	(0.078)
Abilities	Explosive Strength	-0.035	(0.046)	-0.144	(0.093)
Knowledge	Production and Processing	-0.038	(0.089)	0.005	(0.121)
Abilities	Gross Body Equilibrium	-0.049	(0.074)	-0.169	(0.093)
Abilities	Night Vision	-0.051	(0.088)	-0.015	(0.095)
Abilities	Peripheral Vision	-0.056	(0.090)	-0.010	(0.099)

Knowledge	Medicine and Dentistry	-0.061	(0.053)	0.028	(0.105)
Abilities	Visual Color Discrimination	-0.064	(0.122)	0.048	(0.047)
Abilities	Extent Flexibility	-0.067	(0.078)	-0.182	(0.088)
Abilities	Finger Dexterity	-0.068	(0.114)	0.017	(0.047)
Abilities	Gross Body Coordination	-0.090	(0.072)	-0.190	(0.101)
Abilities	Dynamic Strength	-0.099	(0.079)	-0.145	(0.092)
Abilities	Speed of Limb Movement	-0.102	(0.070)	-0.084	(0.103)
Abilities	Static Strength	-0.106	(0.073)	-0.153	(0.107)
Skills	Troubleshooting	-0.108	(0.085)	-0.038	(0.078)
Abilities	Stamina	-0.111	(0.070)	-0.161	(0.106)
Skills	Quality Control Analysis	-0.128	(0.104)	-0.018	(0.073)
Skills	Operation Monitoring	-0.142	(0.067)	-0.014	(0.083)
Abilities	Manual Dexterity	-0.152	(0.111)	-0.035	(0.068)
Abilities	Depth Perception	-0.155	(0.097)	-0.042	(0.083)
Abilities	Multilimb Coordination	-0.156	(0.088)	-0.085	(0.112)
Skills	Operation and Control	-0.166	(0.071)	-0.001	(0.103)
Abilities	Response Orientation	-0.169	(0.088)	-0.061	(0.087)
Abilities	Control Precision	-0.182	(0.105)	-0.011	(0.086)
Abilities	Arm-Hand Steadiness	-0.185	(0.110)	-0.026	(0.064)
Abilities	Wrist-Finger Speed	-0.197	(0.106)	-0.022	(0.060)
Abilities	Reaction Time	-0.225	(0.088)	-0.065	(0.107)
Abilities	Rate Control	-0.251	(0.102)	-0.036	(0.106)

Note.- Estimates of β^s and $\widetilde{\beta^s}$ using Brazilian data. Robust standard errors in parentheses.

Test of non-randomness measure We also use Brazilian data to test the hypothesis that our measures of the non-randomness of immigration are informative. If they are informative, then it will be more likely that the American (Brazilian) estimates for skill s will be larger when the non-randomness tests show greater upwards bias in the American (Brazilian) data.

Because of the small sample of countries in the Brazilian data, we cannot perform the immigration rate non-randomness analysis. However, we can perform the same analysis for young immigrants (ages 0-2 at the time of immigration) that we perform in Section 4 on the US data.

Let β^s_B be the analogue of β^s for Brazilian, as opposed to US, data. Similarly, let $\widetilde{\beta^s_B}$ denote the equivalent of $\widetilde{\beta^s}$, the coefficient in the young immigrants robustness check, for Brazil. Then, for each skill s, we construct

$$\Delta^s = \widehat{\beta^s} - \widehat{\beta^s_B}$$

and

$$\widetilde{\Delta^s} = \widehat{\widetilde{\beta^s}} - \widehat{\widetilde{\beta^s_B}}.$$

Finally, we regress Δ^s on $\widetilde{\Delta^s}$. If our robustness check is informative, then there should be a positive coefficient in this regression, i.e. the country whose data has a larger implied bias should have a larger main result.

The result of this regression is a coefficient of 0.172 with standard error of (0.080), which is significant at the 5% level. This is consistent with the view that the young immigrants robustness check is informative about bias due to non-randomness of immigration.